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**Development and Adoption of Plug-in Electric Vehicles in China:
Markets, Policy, and Innovation**

Submitted in partial fulfillment of the requirements for
the degree of
Doctor of Philosophy
in
Engineering and Public Policy

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*I dedicate this thesis to Wayne and Claire Horton
for the life-changing inspiration they have given to me
and so many others to go abroad, explore, and embrace
the adventure of learning from new perspectives.*

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economics in China has helped me see my research through a different lens, and her feedback throughout much of the third study in particular helped shape the interviews as well as the theoretical contributions of the study. Finally, as my committee co-chairs and the *yin* and *yang*¹ of my advisory team, Jeremy Michalek and Erica Fuchs have both contributed enormously in different ways to the direction of this thesis as well as my own individual growth and development as a researcher. Jeremy has consistently challenged me (and still does) to reach far greater depths in my understand of statistics and econometric modeling than I ever anticipated. His rigor and thoroughness as a researcher has continuously raised the quality of my work to higher and higher standards, and I am grateful for his unwavering encouragement and confidence in me to achieve those standards. Erica has greatly expanded my understanding of major theories by engineers, economists, sociologists, and political scientists on innovation, knowledge transfer, and how firms and nations compete (discussing some of these ideas during an early visit to CMU was one of the reasons I actually chose to join EPP in the first place). I have always admired her ability to see the big picture and integrate ideas and theories across different fields, and I am grateful to have had her guidance in integrating many of the ideas in this thesis. The success of the interdisciplinary work in this thesis is without a doubt a direct result of the combination of different perspectives and approaches to solving tough problems that my whole committee has provided.

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¹I use this analogy not to imply that Erica and Jeremy are opposites, but rather to imply that together they form a remarkably complementary team, each being highly aware of their own and each others' strengths and weaknesses; the balance they achieve as an advisory team is extraordinary.

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Abstract

In recent years, the Chinese government, motivated by rapidly increasing energy demand and limited oil reserves, has promoted policies for energy efficiency and research investments in energy-saving technologies. At the same time, China has become home to distinct forms of downstream industrial innovation in technology commercialization and redefinition. Some evidence suggests that these two themes could be synergistic; that is, developing nations like China—with their differences in consumer preferences and rapidly rising domestic demand—may be able to reduce per-capita energy consumption while contributing to the advancement of the technological and business strategy frontiers. Given the size and growth rate of China’s economy, the environmental and technology implications could be global. Given this context, this thesis is a collection of three papers that assess how characteristics of China’s domestic environment, including consumer preferences, national and local institutions, market characteristics, and policy, are associated with the development and adoption of plug-in vehicles in China.

The first study measures and compares consumer willingness-to-pay for different plug-in vehicle technologies in China and the United States using a conjoint survey fielded in each country. Results show that with the combined bundle of attributes offered by vehicles available today, gasoline vehicles continue in both countries to be most attractive to consumers, and American respondents have significantly lower relative willingness-to-pay for battery electric vehicle (BEV) technology than Chinese respondents. Results also suggest that Chinese respondents are more receptive to today’s full electric vehicles than American respondents, regardless of subsidies. This implies potential for earlier BEV adoption in China, given adequate supply.

The second study builds upon the methods of the first. Using a synthetic data experiment, I explore the benefits of pooling together survey and market sales data in a joint model when there are endogenous parameters in the market data (a commonly cited source of parameter bias in market choice data) and when consumer response to attributes is different in the survey context versus the market for which we want to recover parameters. Results suggest that the presence of these factors can greatly affect

pooled model parameter estimates. I also show that when endogeneity is present in the market data, the likelihood ratio test that is frequently used to justify pooling is neither necessary nor sufficient to determine whether survey and market data should be pooled. I provide new guidelines for understanding under what conditions pooling data sources may or may not be advisable for accurately estimating true market preference parameters, including consideration of the context and conditions under which the data were generated as well as the relative balance of information between data sources.

Finally, in my third study I use sales data, archival data, and 37 qualitative interviews to examine a variety of innovations among independent domestic firms in China's the plug-in vehicle sector. Results suggest that the innovation environment in China may be richer and more diverse than previous scholars have suggested. I observe firms innovating in three distinct directions ("up," "down," and "sideways") with respect to vehicle technology and organizational and business strategy. I theorize that while national institutions such as the joint venture system may be inadvertently discouraging international joint venture firms from entering China's plug-in vehicle sector, regional institutions such as local protectionism may be serving as incubators for a variety of innovations within independent domestic firms in their early development stages; these institutional protections along with demand from China's large, heterogeneous domestic market may help explain the presence of the observed variety of innovations. As these domestic firms begin to grow beyond their protected regional markets, national institutions may need to evolve to support national standardization of policies and plug-in infrastructure.

Keywords: China, Plug-in Electric Vehicles, Consumer Preferences, Willingness-to-Pay, Conjoint Analysis, Discrete Choice Models, Policy, Markets, Innovation.

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Chapter 1

Introduction

As a researcher, I am interested in understanding the forces that shape the development and adoption of technologies that have important energy and environmental implications in China. This thesis focuses on the development and adoption of plug-in electric vehicles as an example of an emerging technology that sits right at this intersection, with implications for reducing both oil consumption and pollution from passenger cars.

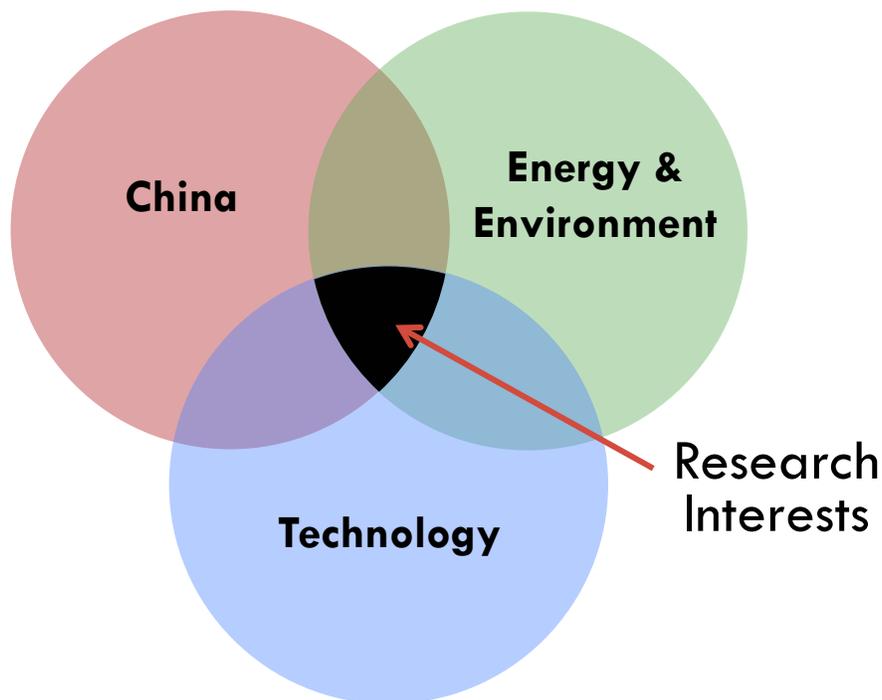


Figure 1.1: Diagram of research interests.

This thesis examines the development and adoption of plug-in vehicles in China from the perspectives of demand and production, recognizing that policy and technology can shape these activities and therefore change the set of economic alternatives that emerge. All of this activity occurs in an institutional context that defines the “rules of the game” [1] by which individuals and firms adhere, including formal rules such as legislation and regulation as well as informal rules such as culture and the street-level interpretation of the formal rules. These rules co-evolve over time and are mutually influential.

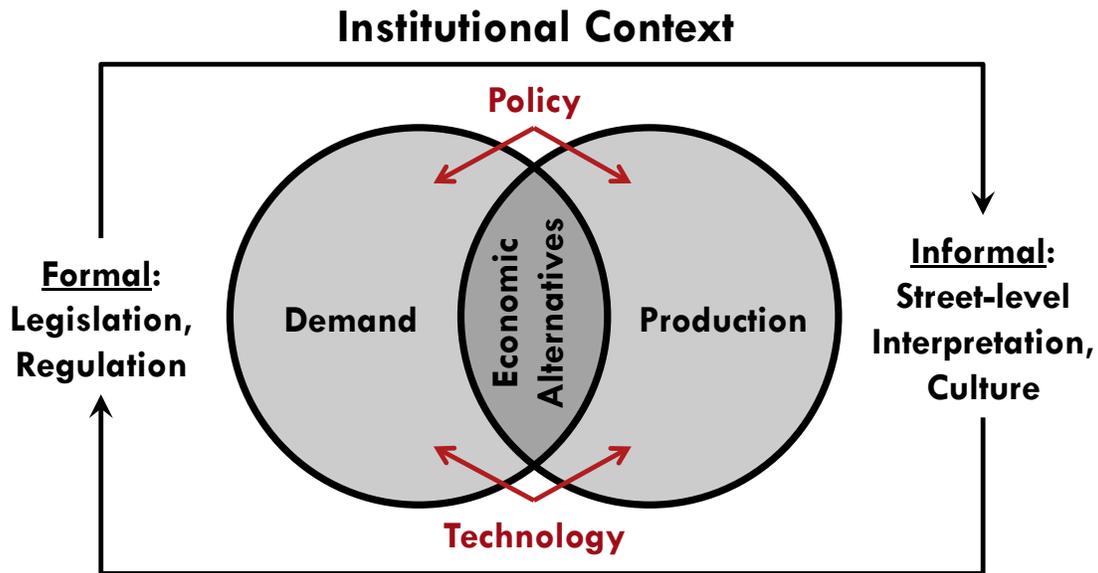


Figure 1.2: Conceptual diagram of thesis.

Given this context, this thesis is a collection of three papers that assess how characteristics of China’s domestic environment, including consumer preferences, national and local institutions, market characteristics, and policy, are associated with the development and adoption of plug-in vehicles in China. Chapter 2 provides background information on the specific types of electric vehicle technologies referenced throughout this thesis as well as a brief history on the growth of China’s automotive industry and policy efforts to develop the plug-in vehicle sector. In Chapter 3, I compare consumer preferences for plug-in vehicles in China and the U.S. by estimating discrete choice models using a conjoint survey I designed and fielded in each country. In Chapter 4, I build upon the methods of Chapter 3 by conducting a synthetic data experiment to test the performance of models that pool survey and market sales data in recovering true preference parameters under conditions that choice modelers are likely to face. Specifically, I explore the benefits of pooling when

there are endogenous parameters in the market data (a commonly cited source of parameter bias in market choice data) and when consumer response to attributes is different in the survey context versus the market for which I want to recover parameters. In Chapter 5, I use sales data, archival data, and 37 qualitative interviews with automotive managers and engineers, government officials, researchers, journalists, and industry consultants to study the variety of innovation directions independent domestic Chinese firms are taking in China’s plug-in vehicle sector. Finally, in Chapter 6 I summarize the contributions of this thesis as well as remaining open questions this thesis raises. Table 1.1 summarizes the three primary research studies that comprise this thesis (Chapters 3 through 5).¹

Table 1.1: Summary of three primary research studies.

Chapter	Topic	Approach	Study Title
3	Demand	Quantitative	Will Subsidies Drive Electric Vehicle Adoption? Measuring Consumer Preferences in the U.S. and China
4	Demand	Methodological	When Should We Pool Revealed and Stated Preference Data? Assessing Endogeneity and Context
5	Production	Qualitative Mixed	Up, Down, and Sideways: Innovation in China and the Case of Plug-in Vehicles

¹As a note to the reader, chapters 3 through 5 are based on published or working papers with co-authors; as such, first person plural is used in these chapters for consistency.

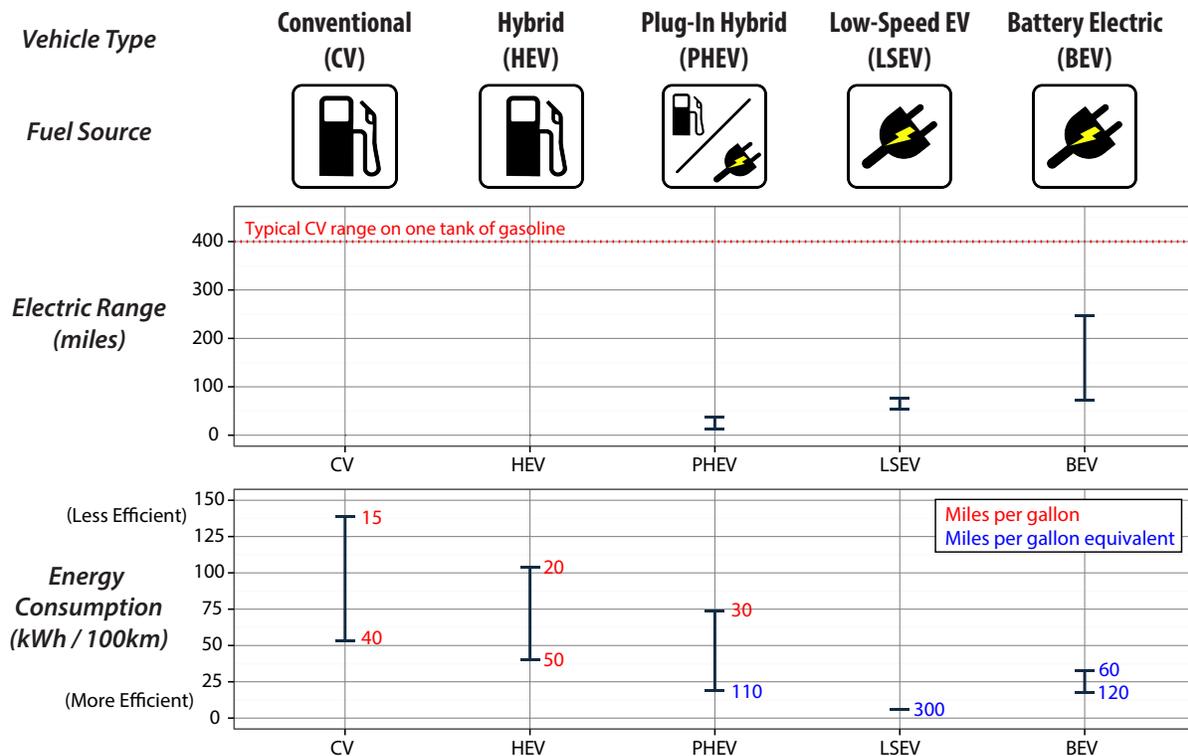
Chapter 2

Background

2.1 Electric Vehicle Technologies

In the context of this thesis, I define “electric vehicles” to include gasoline-powered hybrid electric vehicles (HEVs) as well as several plug-in vehicle technologies: plug-in hybrid vehicles (PHEVs), battery electric vehicles (BEVs), and low-speed electric vehicles (LSEVs). HEVs can only use gasoline as fuel, but they utilize a small battery pack and electric motor to improve fuel efficiency, mostly through regenerative braking, engine downsizing, engine shutoff at idle, and power management. PHEVs are similar to HEVs except they can be plugged into an electrical outlet to charge their battery pack. With larger batteries than HEVs, PHEVs can typically be driven for short distances (usually less than 40 miles) using only or mostly electricity before switching to gasoline for an extended range. BEVs only use electricity and do not use gasoline. They have large electric motors and large battery packs to enable longer driving ranges and must be plugged into an electrical outlet to charge. Finally, LSEVs are a particular subset of BEVs that use older technologies, such as lead acid batteries, and sell at lower prices, often around USD\$5,000 or less. These vehicles are typically micro vehicles that have maximum speeds of less than 50 mph and limited ranges of around 30 - 50 miles. They are also sometimes referred to as “neighborhood electric vehicles.” Figure 2.1 summarizes these technologies.

Parts of the content presented in this chapter have been previously published in Transportation Research Part A: Policy and Practice [2].

Figure 2.1: Electric vehicle technologies.¹

2.2 China's Push for Plug-in Vehicles: Energy Security, Pollution, and Technology Leadership

In just fifteen years since joining the World Trade Organization, China has rapidly grown to become the largest passenger car market in the world, with annual sales growing from less than 1 million in 2001 to over 21 million in 2015 [3]. The size and growth of China's vehicle market should not be expected to stop soon; with approximately 20% of the world's population, China has just 80 vehicles per thousand people, compared to the U.S. which holds less than 5% of the world's population but has 770 vehicles per thousand people [4–6]. Figure 2.2 shows this rapid growth compared to the historic growth in the U.S., the world's second largest automobile market.

China has also become the largest *producer* of vehicles in the world [7]. Today, one out of every four new vehicles in the world are produced in China. These dramatic changes in global demand and production have attracted nearly all of the world's largest automakers, and for some China has become their largest market. For example, sales in China comprised the largest portion of global sales for Volkswagen (36%) and General Motors (37%) in 2015 [8, 9].

¹Electric range and energy consumption from www.fueleconomy.gov.

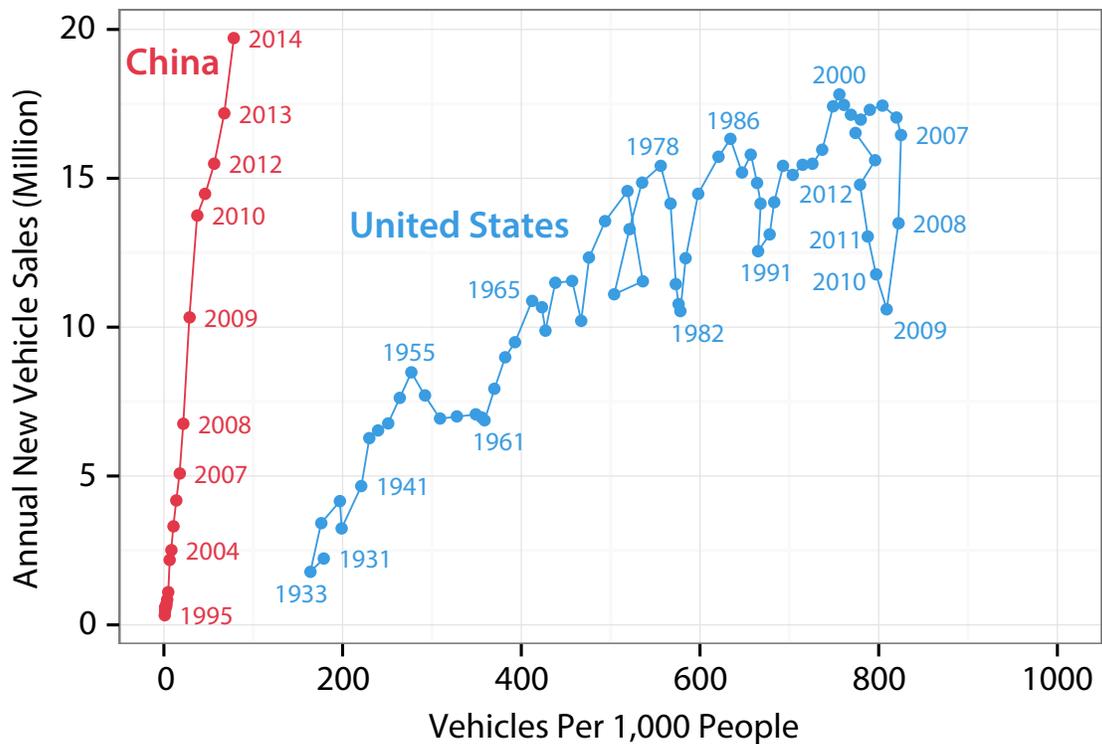


Figure 2.2: Growth in Chinese and U.S. passenger vehicle sales and ownership [4-6].

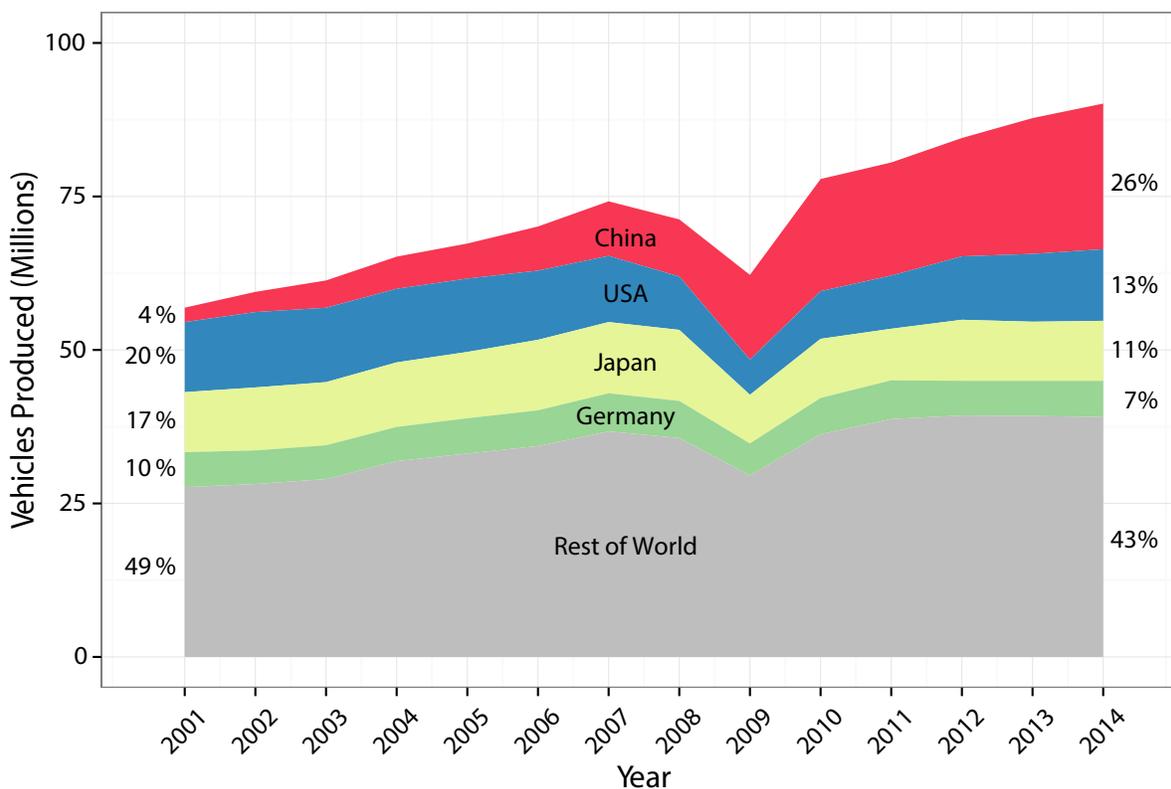


Figure 2.3: Global passenger vehicle production from 2001 to 2014 [7].

While a boon for economic development, this rapid rise in vehicle production and demand in China has been associated with several negative consequences. Passenger vehicles are the largest driver of China’s rapidly increasing demand for oil and consume approximately half of all crude oil used in China [10]. China also now imports approximately 55% of it’s annual oil usage [11], the majority of which comes from the Middle East and travels through the Malacca Straits, leaving China in a strategically risky situation from a national security perspective [12]. Passenger cars are also a major source of pollution. It is estimated that 7% of China’s greenhouse gas (GHG) emissions came from automobiles in 2008 [11], and over half of all volatile organic compound (VOC), carbon monoxide (CO), and nitrogen dioxide NO_x now come from passenger vehicles in China [13].

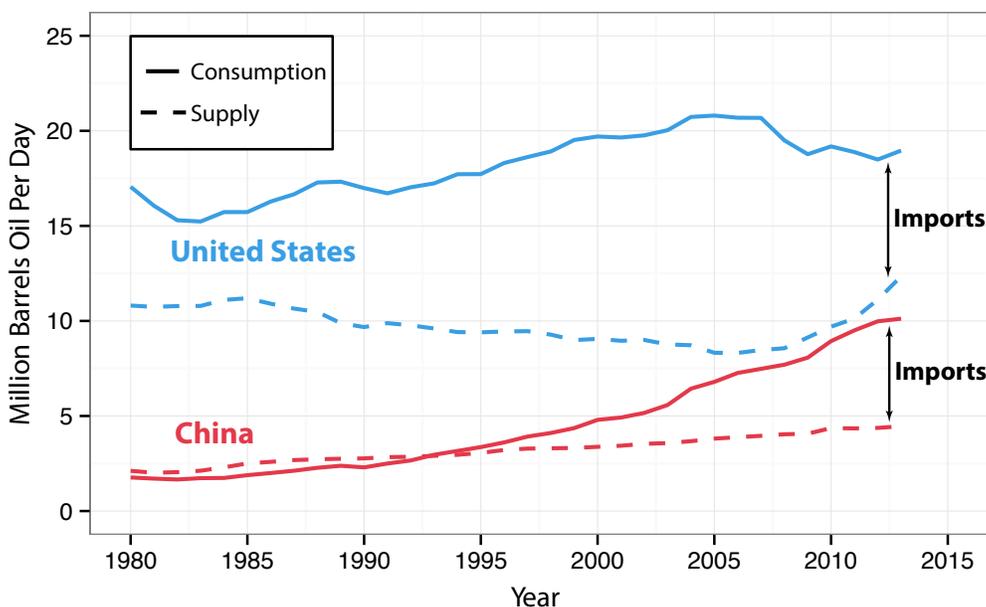


Figure 2.4: Growth in U.S. and China dependency on foreign oil [11].

In response to these harmful impacts from passenger cars, the Chinese government has promoted the development and adoption of plug-in electric vehicles which can use grid electricity for fuel [14]. Plug-in vehicles have become strategically attractive as a way of reducing oil consumption and pollution² from passenger cars while providing Chinese automakers an opportunity to obtain a position of leadership in an emerging technology in the global automotive industry. In terms of global sales, conventional vehicles are still by far the dominant automotive technology; nonetheless, China remains one of the largest markets for emerging plug-in vehicle technologies.

²With 75% of China’s electricity coming from coal-fired power plants, plug-in vehicles may actually on average increase GHG emissions [15,16], although results would vary widely by region [17].

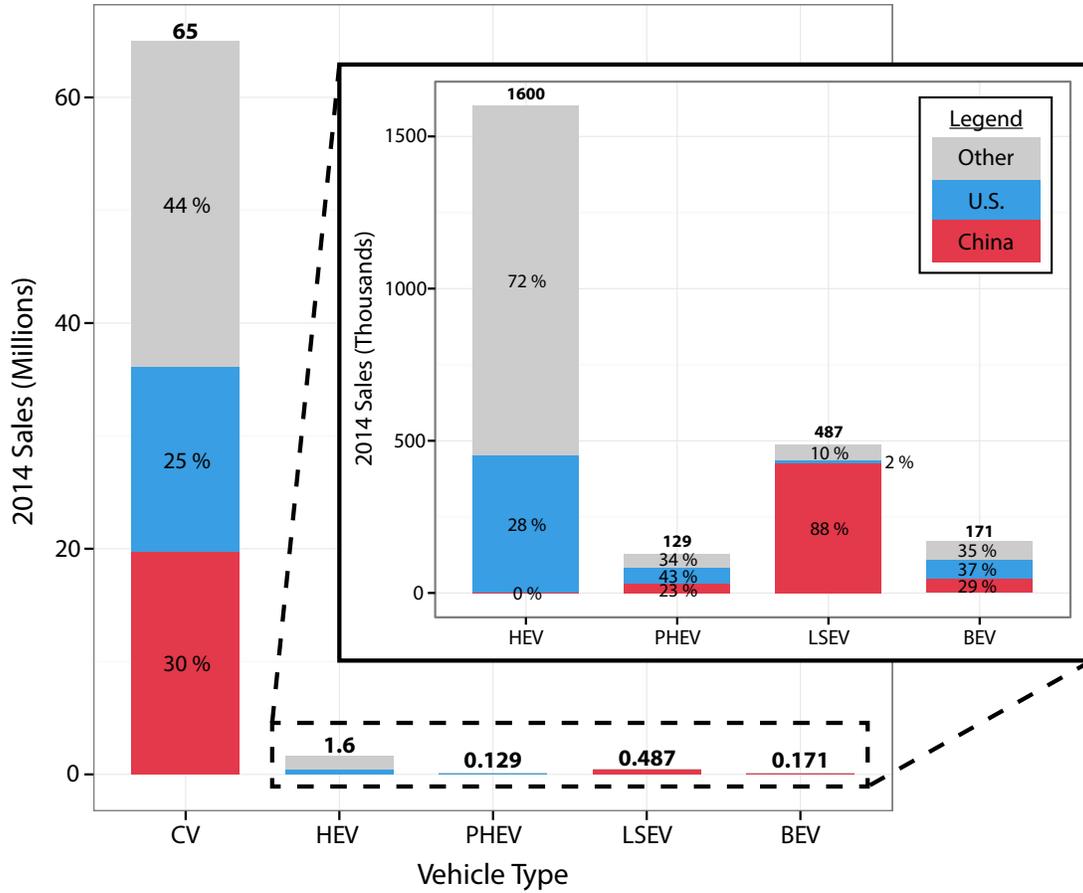


Figure 2.5: 2014 global vehicle sales by technology [3, 18, 19].

2.3 Policy Support for Plug-in Vehicles in China

Over the past decade, domestic plug-in vehicle development has become a cornerstone of Chinese automotive policy, as illustrated by the central government’s remarkably ambitious target of deploying half a million plug-in vehicles (PHEVs and BEVs) by 2015 and 5 million by 2020 [14]. Plug-in vehicles have become strategically attractive due to their unique position as a technology that promises solutions to three critical national priorities: energy security, environmental sustainability, and technological leadership. In particular, Chinese policy makers are hoping for “leapfrogging”—the idea that domestic Chinese automakers could become world leaders in plug-in vehicle technologies without the costly need to develop technical capabilities in traditional vehicle technologies. China’s State Council has linked this vision to its economic development plans, which emphasize industrial upgrading to higher technologies and higher value added roles in global production chains [14, 20].

This push for plug-in vehicles has led to a multitude of policy experiments from various government bureaus aimed at driving the development and adoption of plug-in vehicles forward. Other less direct policies, such as fuel economy standards and automotive production licenses, have also included incentives for plug-in vehicles. Figure 2.6 illustrates the key policies and programs implemented since 1995. For more details of relevant policies, see [20–22]. New energy vehicle policies are managed between four different ministries:

1. The Ministry of Finance (MOF): Provides funding for new energy vehicle R&D and deployment of supporting infrastructure.
2. The Ministry of Science & Technology (MOST): Promotes new energy vehicle R&D primarily through national S&T projects such as the 863 program, China’s primary S&T research funding program.
3. The Ministry of Industry and Information Technology (MIIT): Responsible for vehicle emission monitoring, standards setting (including fuel economy standards), and project appraisal for the auto industry.
4. The National Development and Reform Commission (NDRC): Sets national targets; plays a coordinating role across different bureaus for the new energy vehicle industry.

Some of the earliest new energy vehicle policies came from MOST during China’s 10th Five-Year Plan (2001 - 2005), which established the Electric Vehicle Key Project under the 863 Program and provided \$290 million for new energy vehicle development. By the 11th Five-Year Plan (2006 - 2010), the total funding had grown to \$1.5 billion through a multitude of policy experiments [21]. During this period, the NDRC formally defined the focal new energy vehicle technologies (BEVs, PHEVs, and fuel cell vehicles) and enacted the 2009 Auto Industry Adjustment and Renovation Plan, which set the ambitious target of deploying 500,000 new energy vehicles by 2011.

In response, the MOF and MOST jointly launched the 2009 new energy vehicle demonstration program known as *shi cheng qian liang*³ (“Ten Cities, Thousands of Vehicles”, or TCTV), which was China’s first effort to deploy new energy vehicles in select pilot cities, focusing on public fleet vehicles such as taxis and buses [23]. The original list of 13 Tier I pilot cities was later extended to a total of 25 cities, including 7 Tier II and 5 Tier III cities [24, 25]. Through the pilot program, the

³十城千辆: The program aimed to deploy over 1,000 new energy vehicles in each pilot city, totaling over 10,000 nationwide (hence the name).

central government offered vehicle purchase subsidies while leaving local governments responsible for funding supporting infrastructure such as charging stations. In 2010, the central government opened subsidies to private consumers.

Over the life of the program, actual new energy vehicle deployment fell far below government targets, totaling just 52,623 by 2012 [21]. Rather than establishing a national industry, the TCTV program proved divisive and resulted in strong local protectionism. Most participating cities viewed the program as an opportunity to support their local automotive industry, focusing incentives on new energy vehicles produced by local automakers that each developed their own vehicles to take advantage of the opportunity. A total of 76 automakers and 343 models were approved to receive subsidies, compared to just 17 automakers and 44 models available in the U.S. during the same period [22].

Category	Policy / Event	Government Body	HEV / BEV		HEV				FCV			BEV / PHEV					← Tech Focus				
			9th		10th				11th			12th					← 5 Year Plan				
			96	97	98	99	00	01	02	03	04	05	06	07	08	09	10	11	12	13	14
Industry Support	EV standard technical committee set up to develop EV standards	MIIT																			
	Auto Industry Policy revised; developed "Energy Savings Medium-and Long-Term Plan," which sets auto industry one of top 10 pillar industries for energy conservation	NDRC																			
Market Adoption	十城千辆 = "Ten Cities Thousand Vehicles": Pilot program to deploy over 1,000 PEVs in each of 10 pilot cities (USD\$2.5 billion)	MOF, MOST																			
	Subsidies offered to private buyers for PHEVs & BEVs	MOF																			
	Credits offered for plug-in vehicles to pass the corporate average fuel consumption standard	MIIT																			
R&D	National Electric Vehicle Test and Demonstration Zone Established	MOST																			
	National Clean Vehicle Action Program - HEVs & Natural Gas short term, BEVs mid to-long term	MOST, NDRC, MIIT, MOF																			
	"EV Key Project" included in 863 national high-tech R&D program (USD\$130 million)	MOST																			
	"Alternative Fuel Vehicles Key Project" included in 863 national high-tech R&D program (USD\$165 million)	MOST																			
Strategic Planning	"Three Transverses and Three Longitudes": Transverses = HEVs, BEVs, & FCVs; Longitudes = powertrain, motor, and battery	MOST																			
	State Council adopts Science and Technology Medium- and Long-Term Development Plan	State Council																			
	NDRC defines "New Energy Vehicle" (NEV) to include HEVs, BEVs, & FCVs	NDRC																			
	Set sales targets of 500,000 plug-in vehicles by 2011 and 1 million by 2015	NDRC																			
	Auto Industry Adjustment and Renovation Plan: Set target for 5% of all new vehicle sales to be NEVs	State Council																			
	Focus on PHEVs & BEVs announced in "Development Plan for an Energy Efficient and New Energy Vehicle Industry (2012-2020)"	State Council																			

Figure 2.6: Key Chinese new energy vehicle policies and programs [21, 22].

Today, the central government offers subsidies to private consumers that scale with battery capacity (RMB 3,000 per kWh) and reach a maximum value of RMB 50,000 (U.S. \$8,200) for PHEVs and RMB 60,000 (U.S. \$9,800) for BEVs. Importantly, these subsidies are restricted only to vehicles that adhere to the “Three Transverses and Three Longitudes” R&D strategy implemented by MOST [26]. The “transverses” are three strategic vehicle technologies (BEVs, PHEVs, and fuel cell vehicles) and the longitudes are core components of these technologies (batteries, motors, and battery management systems). To qualify for subsidies, the vehicle drivetrain must use one of the “transverse” technologies, and one of the “longitude” components must be manufactured in China. Given these restrictions, many foreign automakers have been unwilling to bring their most advanced plug-in vehicle technologies to the Chinese market, such as Chevrolet’s *Volt*, a PHEV that uses an in-house manufactured motor and control system and LG Chem batteries from South Korea, or Nissan’s *Leaf*, a BEV that uses battery technology sourced from Japan’s NEC Corporation [27]. LSEVs do not qualify for subsidies, but a new licensing policy implemented in 2015 now allows firms that exclusively produce LSEVs to sell them without a traditional automobile production license [28].

China’s national fuel economy standards set by the MIIT also include incentives for automakers to sell plug-in vehicles. The Corporate Average Fuel Consumption standard requires each automaker to meet a minimum annual average fuel economy across its fleet of vehicles sold. Under the current regulation, sales of plug-in vehicles, which have extremely low fuel consumption, can be counted multiple times to reduce the computed average fleet fuel consumption. The multiplier for BEVs is set at 5 for 2016–2017 and will fall to 3 in 2018–2019 and then to 2 in 2020 while other vehicles such as PHEVs with a combined fuel consumption of 2.8L/100km can be counted 3 times [29].

Finally, on top of federal incentives, some local governments provide a variety of policies to support local plug-in vehicle development. Some local policies include providing lower land costs, local infrastructure support, and support in attaining automotive production licenses for industries related to new energy vehicles.

Chapter 3

Will Subsidies Drive Electric Vehicle Adoption? Measuring Consumer Preferences in the U.S. and China

3.1 Study Overview

In this chapter, we model consumer preferences for conventional vehicle (CV), HEV, PHEV, and BEV vehicle technologies in China and the U.S. using data from choice-based conjoint surveys fielded in 2012–2013 in both countries. We find that with the combined bundle of attributes offered by vehicles available today, gasoline vehicles continue in both countries to be most attractive to consumers, and American respondents have significantly lower relative willingness-to-pay for BEV technology than Chinese respondents. While U.S. and Chinese subsidies are similar, favoring vehicles with larger battery packs, differences in consumer preferences lead to different outcomes. Our results suggest that with or without each country’s 2012–2013 subsidies, Chinese consumers are willing to adopt today’s BEVs and mid-range PHEVs at similar rates relative to their respective gasoline counterparts, whereas American consumers prefer low-range PHEVs despite subsidies. This implies potential for earlier BEV adoption in China, given adequate supply. While there are

The study presented in this chapter has been previously published in Transportation Research Part A: Policy and Practice [2]. The use of first person plural includes coauthors Yimin Liu, Elea Feit, Erica Fuchs, Erica Klampff, and Jeremy Michalek.

clear national security benefits for adoption of BEVs in China, the local and global social impact is unclear. With higher electricity generation emissions in China, a transition to BEVs may reduce oil consumption at the expense of increased air pollution and/or greenhouse gas emissions. On the other hand, demand from China could increase global incentives for electric vehicle technology development with the potential to reduce emissions in countries where electricity generation is associated with lower emissions.

3.2 Introduction

The goal of this chapter is to measure and compare consumer preferences for various electrified vehicle technologies in the U.S. and China. We also consider what hypothetical conditions may be required to drive further mainstream adoption and what the implications would be for policy and global technology trajectories. We model consumer preferences for CV, HEV, PHEV, and BEV technologies in China and the U.S. using data from choice-based conjoint surveys fielded in 2012 and 2013 in both countries. The study addresses three primary research questions:

1. How do U.S. and Chinese preferences for electrified vehicle technologies and attributes compare?
2. How would plug-in vehicles compete against their gasoline counterparts in each country *without* subsidies?
3. How do subsidies influence the competitiveness of plug-in vehicles vs. their gasoline counterparts?

We address question 1 by estimating consumer WTP for incremental changes in vehicle attributes based on the conjoint data we collected, and we address questions 2 and 3 by conducting market simulations where pairs of selected plug-in vehicles and their gasoline counterparts compete against one another in the U.S. and Chinese markets, both with and without subsidies.

3.3 Methods

Given the limited history of plug-in vehicle sales in the U.S. and China and the complications of regional regulations, supply limitations, incentives, mandates, and non-representative early-adopter preferences, historical sales data offer limited information about potential mainstream adoption

of electrified vehicles. Stated choice methods provide an alternative approach for understanding potential future mainstream adoption. For these reasons, we use choice-based conjoint (CBC) analysis to measure consumer preferences.

In CBC analysis, participants in a survey experiment are asked to compare several product profiles (each defined by a set of attributes, such as price, brand, type, etc.) and choose the product they are most likely to buy. Discrete choice models are then used to infer the relative importance of each attribute in determining consumer choice [30]. Because the experiment is controlled, we avoid many of the pitfalls of using historic sales data, such as multicollinearity, endogeneity, missing attributes, and a lack of information about consumers, the attributes they observed, and the alternatives they considered [31, 32]. However, the major disadvantage of controlled conjoint experiments is the potential difference between a consumer’s choice behavior in the hypothetical survey conditions we create versus choice behavior in the market when real money is being spent in the point-of-purchase context. We attempt to mitigate these sources of error by targeting new car buyers and presenting choice questions in a way that mimics real purchase decisions (choose one among a set of concrete alternatives). For this research, we designed and fielded equivalent controlled survey experiments in China and the U.S. during the summer of 2012 and spring of 2013.

3.3.1 Literature on Measuring Vehicle Preferences

Many previous studies have applied conjoint analysis and/or discrete choice models to examine automobile demand. Lave and Train (1979) were the first to apply a multinomial logit model to survey data of new car buyers to examine how vehicle attributes and consumer covariates influence choice [33]. Boyd and Mellman (1980) extended the multinomial logit model using the hedonic demand model, also known as the “random coefficients logit model,” which incorporates variation in consumer tastes and preferences [34]. Others further improved upon these modeling techniques by using mixed logit models, which allow for more flexible substitution patterns [35, 36]. Berry et al. (1995) proposed a method to deal with endogeneity, which enables regression based on market data rather than survey data [37]. Other model classes have also been applied, such as the multiple discrete-continuous extreme value (MDCEV) model used to model vehicle type and use in cases where households may hold multiple vehicle types with different usage patterns [38, 39]. Over time, the literature has expanded beyond examining vehicle attributes to stress the importance of

consumer characteristics such as travel attitude, personality, lifestyle, and mobility [40] as well as socio-demographic factors and environmental awareness [41] as important factors that affect vehicle type choice.

Consumer preference models have been used to study multiple topics in the automotive industry. McCarthy (1996) uses a multinomial logit demand model on data from a 1989 nationwide household survey of new vehicle buyers to examine the market price elasticity of demand for automobiles [42]. Goldberg (1998) uses a discrete choice model of auto demand and a continuous model of vehicle utilization from the Consumer Expenditure Survey (1984-1990) to examine the effects of CAFE standards on automobile sales, prices, and fuel consumption [43]. Train and Winston (2007) employ a mixed logit demand model to study the relation between the consumer choice behavior and market share drops of the U.S. automakers in the past decade [44].

More recent studies have focused on demand for alternative-fuel vehicles (AFVs). Golob et al. (1997) use conjoint analysis to examine fleet demand of AFVs [45]. Others have examined AFVs by combining stated and revealed preference data using multinomial logit and mixed logit models [46, 47]. Other methods have used interactive surveys to investigate consumer awareness of and preferences towards AFVs [48].

The majority of studies examining AFVs have been focused on the United States, with only a few in other countries: Ziegler (2012) in Germany [41]; Dagsvik and Liu (2009) in Shanghai, China [49]; and Axsen et al. (2009) in Canada [47]. Comparing results across such studies, however, is challenging because each has differences in survey designs, research objectives, and timing. Our study enables direct comparison of Chinese and American preferences since the surveys fielded in each country were identical in presentation and were fielded during relatively close time periods. Thus, the results for each country are directly placed in a comparative context.

3.3.2 Survey Design

In designing the choice experiment we sought to balance three study goals: 1) provide sufficient information about consumer preferences, 2) match as closely as possible the survey-taker's experience to the experience of making product choices in the marketplace, and 3) limit the cognitive burden on the respondent. Guided by results from several preparatory interviews and pilot surveys conducted in the spring of 2012, we designed a field experiment with three main parts: 1) a vehi-

cle image section, 2) a choice experiment section, and 3) questions on demographics, experience, knowledge, and attitudes towards driving and electrified vehicles. To facilitate comparisons, the survey design was created to be as similar as possible across the two countries. In addition, we also recorded information about each respondent’s previous vehicle purchases as well as daily and annual vehicle miles traveled (VMT). We describe each part in turn.

Part 1: Vehicle Image Selection

Given the limited number of HEVs, PHEVs, and BEVs currently available in the market, some respondents might assume an associated vehicle aesthetic when considering a powertrain type (e.g. visualizing a Toyota *Prius* when shown an alternative with an HEV powertrain). To control for potential bias from inferred vehicle aesthetics or size / class, we ask respondents early in the survey to choose a vehicle class and select an image of a vehicle they found visually appealing. Once selected, we hold this image fixed at the top of each choice question, informing respondents that each vehicle is exactly the same except for differences in the attributes shown in the choice question (similar to selecting a vehicle options package). This isolates the effect of the attributes from aesthetic or vehicle class choices.

Part 2: Choice Experiment

The choice section of the conjoint survey consisted of one “warm-up” choice task and 15 choice tasks used in model estimation, with three options in each choice task. We chose this design as a compromise between collecting sufficient data to estimate heterogeneous models and avoiding excessive cognitive load.¹ The “warm-up” choice task was always shown first and included a clearly dominant alternative (i.e. all attributes identical across alternatives except one was cheaper and more efficient). This warm-up was used as a screening question to identify respondents who did not understand the task or did not take it seriously. Figure 3.1 below is an example of a choice task for the U.S. survey.

¹The literature is mixed on how many questions respondents can reasonably answer. While Bradley and Daly (1994) find a fatigue effect after too many questions, Hess et al. (2012) find the contrary: that such an effect is over-stated in related literature and perhaps non-existent [50,51]. Given the lack definitive guidance in the literature, we relied on our pilot surveys, which suggested that 15 was an acceptable number of questions while 20 garnered respondent complaints about length.

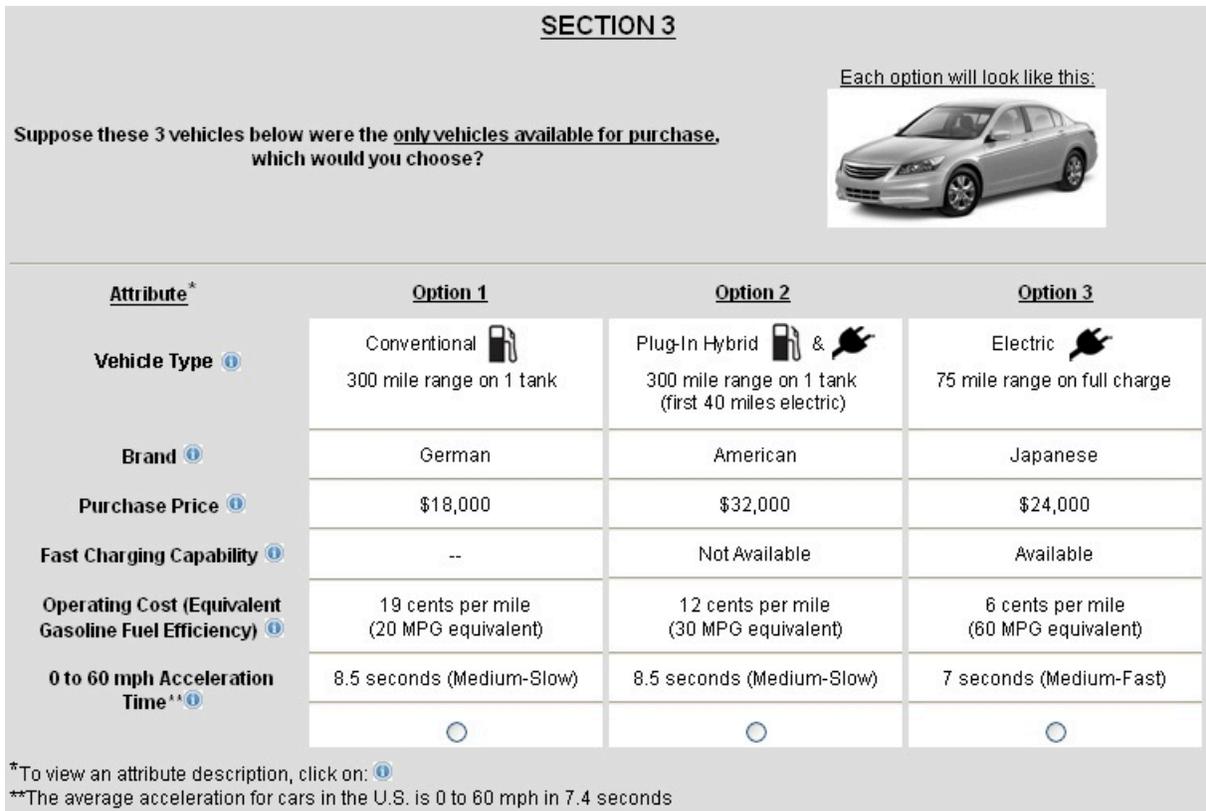


Figure 3.1: Example choice task for the U.S. survey (see Appendix A.5 for the equivalent example in Chinese). The attribute values (levels) in each choice task were randomly assigned for each question and each respondent.

Each alternative has six attributes: type, brand, purchase price, fast charging capability, fuel cost, and acceleration. We chose these attributes for the following reasons. Type, purchase price, fast charging capability, and fuel cost are all necessary attributes to address our research questions, and brand and acceleration were included as critically important attributes influencing choice (informed by pilot surveys and past literature). Vehicle range is treated not as a separate attribute but rather as a component of the vehicle type attribute. The experiment design was fully randomized, meaning that the combination of attribute levels shown for any given alternative for any respondent was randomly selected from the set of all possible combinations.² For vehicle type, we included CVs and HEVs as well as PHEVs and BEVs with varying all-electric range (AER). The AERs for the China survey were given in the km equivalent of the U.S. ranges (within 5% difference due to

²While other experimental designs may have yielded more main-effects information, we chose a randomized design that is nearly orthogonal, which allows us to explore interaction effects between attributes and avoids confounding main effects with interaction effects [52]. The questions were randomized for each respondent, which has been shown to increase efficiency for mixed logit models [53] and may compensate for any loss in efficiency relative to a fixed main-effects design.

rounding in the associated unit). “Brand” was represented using country of origin (e.g.: Volkswagen would be “German,” and Ford would be “American”) to maintain a statistically manageable number of alternatives. The “Fast Charging Capability” attribute was a binary attribute indicating whether or not a plug-in vehicle had the ability to charge in under 15 minutes (the attribute was hidden for CV and HEV powertrains). Operating cost was presented as cost per mile driven due to the mixed fuel types of the different vehicles. The cost-equivalent fuel economy for a conventional gasoline vehicle was provided in parenthesis for reference, since it is a more familiar metric for respondents. The cost-equivalent fuel economy was computed using 2012 average gasoline prices in each country (\$3.60/gal in the U.S. and 7.08 RMB/L (\$4.40/gal) in China) and was presented in the most commonly used form for each country (miles/gallon in the U.S. and L/100km in China). Finally, acceleration performance was provided as the time to accelerate from 0 to 60 miles per hour in the U.S. (0 to 100 kilometers per hour in China).

For each attribute we included levels that were appropriate for the country. The levels were the same across all surveys for vehicle type, brand, and fast charging capability but were different between each country for purchase price, operating cost, and acceleration time. We chose the levels for these attributes based on the respective sales distributions of vehicles in the 2011 market of each country (approximately the 5th, 25th, 50th, 75th, and 95th percentile values in each case). Table 3.1 below summarizes the attributes and levels used in each country for the experiment. While we fielded both car and SUV surveys, based on each respondent’s indicated preference, we discuss only results of the car surveys here because (1) we received fewer SUV responses, particularly in China, and (2) electric vehicles are being implemented first in cars.

Part 3: Questions on Demographics, Experience, Knowledge, and Attitudes

The last section of the survey contained demographic questions as well as questions related to personal experience, attitudes, and knowledge about driving and electrified vehicles. We use a 5-point Likert scale to rate preferences for attributes not included in the choice section, including storage space, reliability, safety, towing capacity, and outward appearance. We used the same scale to ask about environmental attitudes. We also asked about access to parking, access to vehicle charging, income, sex, age, household size, zip code, education level, number of children, and marital status. The full survey text is presented in Appendix A.4.

Table 3.1: Attributes and levels used in U.S. & China choice experiments

Attribute	Levels	
	U.S.	China
Purchase Price	15 / 18 / 24 / 32 /50 (\$1000 USD)	60 / 90 / 130 / 170/ 250 (¥1000 RMB)
Operating Cost	6 / 9 / 12/ 19 (¢/mile)	34 / 42 / 49 / 61 (分/km)
Acceleration Time	5.5 / 7 / 8.5 / 10 (0-60 mph, sec)	9 / 11 / 13 / 15 (0-100 km/h, sec)
Vehicle Type with AER	CV / HEV / PHEV10 / PHEV20 / PHEV40 / BEV75 / BEV100 / BEV150 (AER in miles)	CV / HEV / PHEV15 / PHEV30 / PHEV60 / BEV120 / BEV160 / BEV240 (AER in km)
Brand	German / American / Japanese / Chinese / S. Korean	
Fast Charging Capability	Available / Not Available (applicable for PEVs only)	

3.3.3 Data Collection

The goal of our sampling strategy was to approximate the population of new car buyers in each country rather than identify a representative sample of citizens. In China, the population of new car buyers is concentrated in large urban centers, so we conducted surveys in person in July and August 2012 using laptop computers in four major cities: Beijing, Shanghai, Shenzhen, and Chengdu. We chose these cities for their large passenger vehicle market size, which together account for 35% of 2010 national sales in China, as well as geographic diversity [54]. In each city, we visited large passenger car markets and surveyed respondents walking through the market, screening first for people who reported being in the market for a new vehicle. In the US, the new car buying market is more diverse and not concentrated in cities, so we took a two-pronged sampling approach. First, we sampled users on Amazon Mechanical Turk (AMT) in September 2012 with the goal of achieving a geographically diverse sample as well as a mix of urban, suburban, and rural new car buyers. We supplemented this sample with an in-person sample in February 2013 at the Pittsburgh Auto Show. Unlike some larger auto shows, the Pittsburgh auto show features primarily mainstream vehicles rather than high-end or concept vehicles, and the audience attracted is composed primarily of ordinary new car buyers rather than auto hobbyists or enthusiasts. We collected the auto show sample primarily to have a U.S. on-the-ground comparison sample to the China sample. We also found that we over-sampled younger, less-wealthy respondents online, so the auto show sample was able to help capture additional older and wealthier U.S. respondents.

In each country, a percentage of the respondents who completed the survey were eliminated

from our analysis due to issues with their responses, including: 1) completing the survey in under 6 minutes (the approximate minimum time for completing the survey without randomly answering the choice questions)³, or 2) failing to choose the dominant choice in the example question which was fixed for each respondent, indicating that the respondent either misunderstood the task or did not pay close attention to the choice question. All respondents in both countries were screened to have had purchased a car within the last year or have intentions of purchasing a car within the next two years. In both countries respondents filled out computer-based surveys that were equivalent in content and in presentation except for language (English in the U.S., Mandarin Chinese in China) and the values of the attribute levels. The translation of the original English survey into Mandarin was performed by one translator and was subsequently back-translated into English by another translator to assess the translation and ensure equivalent language and descriptions in both surveys. Disputes in translation were resolved by discussion with both translators and within the author team.

In the U.S. we collected 312 respondents online and 103 at the Pittsburgh auto show for a total of 415. We discarded 29 online and 2 at the auto show (7.5% of total) based on screening criteria for a total sample size of 384. In China we collected 667 respondents across the four cities and discarded 95 (14%) based on screening criteria for a total of 572 qualified respondents. Of these, we then discarded all remaining data collected in Beijing (124 respondents) since those data appear to include many random responses. The problems with the Beijing data may have been driven by a number of influences. First, Beijing was the only city for which the surveys were fielded outside in the sun on hot summer days, making it uncomfortable and difficult to take the survey. Second, Beijing was the only city for which the authors were unable to be present to ensure the survey was correctly set up and administered. If we include the Beijing data, we find that all effects in China remain comparable, but just larger in magnitude. With the Beijing data removed, our China sample was 448. About two-thirds of the respondents in all four Chinese cities were first-time vehicle buyers, versus only approximately 4% in the U.S.

We compared the age and income distributions of our U.S. and China samples to those of a much larger, representative new car buyer survey obtained from Ford Motor Company and found that we over sampled younger, less wealthy individuals in both countries, with particularly strong

³Pilot studies informed expected survey completion times.

oversampling of this population in the U.S. To account for these differences, we weighted the respondents using least squares optimization to match the age and income cumulative distribution functions from our survey to those from the larger survey as closely as possible subject to lower and upper bounds on the weights to avoid placing too much weight on any one respondent. Details of the procedure and a comparison of the resulting distributions are provided in Appendix A.2.

Table 3.2: Summary of sample demographic information in our survey, our weighted results, and the reference survey (standard deviation is shown in parentheses).

	U.S.			China		
	Our Sample	Weighted Sample	Reference Sample	Our Sample	Weighted Sample	Reference Sample
Household Income	57.3 (29.3)	74.3 (28.7)	74.8 (27.3)	24.1 (15.7)	26.1 (18)	26.1 (17.6)
Age	33.9 (12.7)	51 (14.8)	53.1 (15.4)	33.3 (10.6)	34.8 (7.8)	35.1 (7.8)
Number of Children	0.6 (1.1)	1.4 (1.4)	0.4 (0.8)	0.6 (0.6)	0.7 (0.6)	0.7 (0.6)
Number of Vehicles	1.8 (0.8)	2 (0.7)	–	0.4 (0.6)	0.5 (0.7)	–
Daily VMT	22.9 (10.4)	23.3 (11.4)	–	–	–	–
Annual VMT	11,200 (4,800)	12,461 (4,628)	11,386 (6,377)	–	–	10,609 (5,995)
Household Size	2.7 (1.3)	2.7 (1.2)	2.5 (1.2)	3.3 (1.1)	3.3 (1.2)	3.2 (1)
Years Education	7.2 (1.9)	7.9 (2.3)	7.2 (2.3)	5.9 (1.9)	6 (1.8)	5.9 (2)
Percent Female	35.30%	32.60%	39.30%	39.40%	41.10%	28.70%
Percent Married	44.60%	68.90%	73.50%	55.10%	70.20%	85.60%
Percent with No Children	72.10%	40.30%	75.00%	52.20%	36.50%	36.40%
Percent College Graduates	52.30%	71.20%	53.70%	30.60%	33.10%	34.40%
Percent First Time Buyers	4.40%	1.30%	–	65.40%	59.20%	–
n	384	384	161,903	448	448	13,469

3.3.4 Model Specification

Using a random utility model, we assume each consumer n on each choice situation t will select among a set of alternatives $j \in J_{nt}$ the one that offers the greatest utility u_{njt} :

$$u_{njt} = v_{njt} + \varepsilon_{njt}, \quad j \in J_{nt} \tag{3.1}$$

Here, utility is decomposed into an observable component v_{njt} and an unobservable component

ε_{njt} . The observable component is a function of the observable attributes of the product \mathbf{x}_{jt} , so that $v_{njt} = f_n(\mathbf{x}_{jt})$. The unobservable component, which captures the factors not included in v_{njt} , is treated as a random variable. Utility u_{njt} is therefore a random variable, and the probability that consumer n will select product j on choice situation t is the probability that $u_{njt} > u_{nkt} \quad \forall k \in J_{nt} \setminus j$.

The observable component v_{njt} is often presumed to be linear, so that $v_{njt} = \boldsymbol{\beta}'_n \mathbf{x}_{jt}$, where $\boldsymbol{\beta}_n$ is a vector of coefficients that define the relative importance of the product attributes \mathbf{x}_{jt} in driving choice. The linear assumption on v_{njt} results in what is known as a “preference” space model, where the estimated coefficients for $\boldsymbol{\beta}_n$ are measured in units of utility. For this study, we use a “willingness-to-pay” (WTP) space model for which the coefficients are in units of dollars—a more intuitive unit of comparison.⁴ This specification takes the form of $v_{njt} = \alpha_n(p_{jt} + \boldsymbol{\omega}'_n \mathbf{x}_{jt})$, where α_n is the estimated coefficient for price, p_{jt} is the price attribute, \mathbf{x}_{jt} is the vector of all other attributes, and $\boldsymbol{\omega}_n$ is the vector of WTP coefficients, which could equivalently be represented as $\boldsymbol{\beta}_n/\alpha_n$ [55].⁵

We employ variants of the logit model (one of the most widely adopted choice models), which assume that the unobservable utility ε_{njt} has an independent and identically distributed extreme value distribution, yielding a closed-form expression for choice probabilities given by

$$P_{nit} = \frac{e^{v_{nit}}}{\sum_{j \in J_{nt}} e^{v_{njt}}} \quad (3.2)$$

In order to relax some limiting assumptions from the basic logit model (e.g. the independence from irrelevant alternatives (IIA) property [30]), we also apply a random coefficients mixed logit model [36] in the WTP space, which allows for heterogeneity of preferences across the population and more general substitution patterns. While the basic logit model effectively assumes $\boldsymbol{\omega}_n = \boldsymbol{\omega} \quad \forall n$ and captures variation in WTP across individuals only in the error term ε_{njt} , the mixed logit model instead assumes that the $\boldsymbol{\omega}_n$ coefficients are drawn from a parametric distribution.⁶ Following convention, we assume each element ω_{nj} of the vector $\boldsymbol{\omega}_n$ is drawn from an independent normal distribution, where $\omega_{nj} \sim N(\mu_n, \sigma_n^2)$. We assume a fixed (non-random) α_n coefficient for all

⁴Section 4.4.1 in Chapter 4 provides more detail on the preference and WTP space models.

⁵For comparison, we also estimate equivalent models in the preference space. Results are shown in Appendix A.1.

⁶Models that include interactions with consumer covariates can also capture variation of preferences across consumers.

mixed logit models. While WTP could also be computed from a preference space mixed logit model post-hoc, Train and Weeks (2005) show that such estimates have unreasonably large variance in comparison to those from a WTP space model [55].

Equation 3.3 below shows the explicit model used for this study, with explanations of variable names shown in Table 3.3. Parameters are estimated through maximum likelihood estimation. It is important to note that because v_{njt} is nonlinear in parameters in the WTP space, multiple local maxima could exist, so we use a randomized multistart algorithm to search for a global solution. The full estimation procedure is described in Appendix A.2.

$$\begin{aligned}
 \text{Price:} \quad & v_{njt} = \alpha_n p_{jt} + \alpha_n [\\
 \text{Type:} \quad & \omega_{n1} x_{jt}^{\text{HEV}} + \omega_{n2} x_{jt}^{\text{PHEV10}} + \omega_{n3} x_{jt}^{\text{PHEV20}} + \omega_{n4} x_{jt}^{\text{PHEV40}} + \\
 & \omega_{n5} x_{jt}^{\text{BEV75}} + \omega_{n6} x_{jt}^{\text{BEV100}} + \omega_{n7} x_{jt}^{\text{BEV150}} + \\
 \text{Fast Charging} \quad & \omega_{n8} (x_{jt}^{\text{PHEV10}} + x_{jt}^{\text{PHEV20}} + x_{jt}^{\text{PHEV40}}) x_{jt}^{\text{FASTCHARGE}} + \\
 \text{Capability:} \quad & \omega_{n9} (x_{jt}^{\text{BEV75}} + x_{jt}^{\text{BEV100}} + x_{jt}^{\text{BEV150}}) x_{jt}^{\text{FASTCHARGE}} + \\
 \text{Performance:} \quad & \omega_{n10} x_{jt}^{\text{OPCOST}} + \omega_{n11} x_{jt}^{\text{ACCEL}} + \\
 \text{Brand:} \quad & \omega_{n12} x_{jt}^{\text{AMERICAN}} + \omega_{n13} x_{jt}^{\text{JAPANESE}} + \omega_{n14} x_{jt}^{\text{CHINESE}} + \\
 & \omega_{n15} x_{jt}^{\text{S.KOREAN}}] + \\
 \text{Error:} \quad & \varepsilon_{njt}
 \end{aligned} \tag{3.3}$$

3.4 Results

Using the model from equation 3.3, we investigate model fit between multinomial logit (MNL) and mixed logit (MXL) models, interpret the model coefficients, and examine the influence of consumer demographic, experience, and attitude information on preferences. We estimate each model for China and the U.S. separately, and because the estimates are in the WTP space they can be directly compared without worry over difference in error scale. Each model is estimated using the data from all respondents from each respective country excluding the Beijing sample and invalid responses. In model 1, we fit a MNL model with fixed coefficients for all covariates as in Equation 3.3. In model 2, we fit a MXL model with a fixed price parameter and all other coefficients modeled as independently normally distributed (so the estimated parameters are the mean and variance of

Table 3.3: Description of model variables

Variable	Description
p_{jt}	Price paid in thousands of US dollars
x_{jt}^{HEV}	Dummy for HEV vehicle type {1: yes, 0: no} (base level is CV)
$x_{jt}^{\text{PHEV}\#}$	Dummy for PHEV vehicle type with AER of # miles {1: yes, 0: no} (base level is CV)*
$x_{jt}^{\text{BEV}\#}$	Dummy for BEV vehicle type with AER of # miles {1: yes, 0: no} (base level is CV)*
$x_{jt}^{\text{FASTCHARGE}}$	Dummy for whether a vehicle can be rapidly charged in less than 15 minutes {1: yes, 0: no}
x_{jt}^{OPCOST}	Operating cost in US cents per mile
x_{jt}^{ACCEL}	Time required to accelerate from 0 to 60 mph or 0 to 100 km/hr (seconds)
x_{jt}^{AMERICAN}	Dummy for brand of American origin {1: yes, 0: no} (base level is German)
x_{jt}^{JAPANESE}	Dummy for brand of Japanese origin {1: yes, 0: no} (base level is German)
x_{jt}^{CHINESE}	Dummy for brand of Chinese origin {1: yes, 0: no} (base level is German)
x_{jt}^{SKOREAN}	Dummy for brand of S. Korean origin {1: yes, 0: no} (base level is German)

* The electric range is shown in miles, though the Chinese survey was in km (see Table 3.1). We model everything in U.S. units for comparability.

the distribution for each coefficient). In each model we weight the sample to match income and age distributions from the new car buyer reference sample (unweighted model coefficients are provided in the supplemental information). The estimates from models 1 and 2 for the U.S. and China are presented in Table 3.4. We present the coefficients as μ and σ , referring to the parameters of the assumed distribution on γ_n (e.g. $\omega_{nj} \sim N(\mu_n, \sigma_n^2)$). For the MNL models, $\gamma = \mu$ and $\sigma = 0$.

Comparing fit across the models, the log-likelihood increases when moving from a fixed coefficient MNL model (model 1) to a MXL model with random coefficients (model 2), indicating a better fit to the data (as is expected since the MXL models have more parameters). The Akaike information criterion (AIC) also decreases, suggesting the MXL models do not over-fit the data compared to the MNL models. Another metric for comparing model fit is the McFadden's R-squared (MR^2), which is a measure of how much better the estimated model fits the data compared to the null model with all parameters set to zero (the adjusted MR^2 adjusts for the number of model parameters). For both countries, the MR^2 values of the MXL models are better than those of the MNL models, further suggesting that the MXL models better fit the data compared to the MNL models.

Going forward, we focus on predictions based on model 2 because in addition to having the better log-likelihood values and AIC, they also avoid the IIA assumption inherent in the MNL

models and capture some level of preference heterogeneity in the samples. While we discuss in depth the results from model 2, the following observations can be made across all models:

1. Both U.S. and Chinese consumers dislike BEV₇₅ and BEV₁₀₀ options relative to alternatives and prefer lower price, operating cost, and acceleration time as well as fast-charging capabilities for both PHEVs and BEVs.⁷
2. Compared to Chinese consumers, U.S. consumers have substantially more disutility for BEV powertrains and are less sensitive to acceleration, operating cost, and fast-charging capabilities for both PHEVs and BEVs.
3. Brand is an important factor for both American and Chinese consumers. Americans have stronger preferences for American, German, and Japanese brands and against Chinese and S. Korean brands, while Chinese consumers have stronger preferences for German brands and against Japanese and South Korean brands.

In addition to models 1 and 2, we also estimate several MNL models (models 3 - 8) where we interact vehicle attributes (vehicle type, price, and operating cost) with respondent characteristics to examine differences in preferences for different groups of individuals. We run these models in the preference space with the linear observable utility function $v_{njt} = \beta'_n \mathbf{x}_{jt}$ because it is easier to separate out groups by their characteristics in this framework. Model 3 is the base case with no respondent interactions. Models 4 – 6 interact the demographic variables income, age, and all other demographic variables, respectively; we separate out income and age from all others to avoid multicollinearity in the models. Model 7 interacts respondent covariates that deal with their past driving experience, and model 8 interacts attitude covariates about environmental friendliness and social status. All model estimates for the U.S. and China are shown in Appendix A.1.

Broadly, we find that U.S. respondents are less sensitive to price and operating cost if they are older, have higher incomes, have higher education, own more vehicles, and have children. Higher income respondents are also more opposed to any electrified vehicle technology (HEV, PHEV, or BEV, regardless of range) compared to lower income buyers. The effect on electrified technologies is so strong that after accounting for income differences the lower income group has a positive effect for HEV and PHEV technologies relative to CVs, *ceteris paribus*.⁸ Because electrified vehicles

⁷Preference for fast charging capability for BEVs is not significant in the U.S.

⁸Because a majority of the higher income buyers in our sample are from the Pittsburgh Auto Show, this effect may only be local to car buyers near Pittsburgh.

Table 3.4: Regression coefficient for weighted U.S. and China models in the WTP space

Attribute	Coef.	Model 1: MNL		Model 2: MXL	
		U.S.	China	U.S.	China
Price	μ	0.052 (0.002)***	0.033 (0.002)***	0.066 (0.003)***	0.039 (0.002)***
HEV	μ	-1.176 (1.611)	4.882 (1.917)	-0.418 (1.585)	4.962 (1.992)
	σ	–	–	0.188 (4.664)	19.403 (7.723)
PHEV10	μ	0.027 (1.782)	-1.291 (2.069)	0.822 (1.796)	-1.748 (2.098)
	σ	–	–	2.197 (5.428)	6.055 (8.872)
PHEV20	μ	1.695 (1.751)	-1.242 (2.031)	3.207 (1.734)	-2.245 (2.074)
	σ	–	–	8.664 (5.719)	4.041 (6.792)
PHEV40	μ	2.650 (1.774)	0.930 (2.023)	3.304 (1.741)	0.380 (2.039)
	σ	–	–	7.141 (5.466)	9.108 (6.179)
BEV75	μ	-20.137 (1.978)***	-6.032 (2.088)***	-18.453 (1.934)***	-7.627 (2.365)***
	σ	–	–	4.175 (6.232)	29.843 (7.417)***
BEV100	μ	-19.496 (1.984)***	-8.151 (2.144)***	-18.947 (1.965)***	-10.377 (2.286)***
	σ	–	–	1.898 (5.368)	8.600 (7.340)
BEV150	μ	-13.691 (1.959)***	1.305 (2.050)	-12.727 (1.959)***	0.616 (2.075)
	σ	–	–	10.486 (6.061)	6.973 (6.406)
American	μ	8.188 (1.289)***	-10.574 (1.560)***	7.432 (1.268)***	-7.612 (1.687)***
	σ	–	–	0.665 (3.439)	19.299 (5.866)***
Japanese	μ	0.934 (1.289)	-18.098 (1.689)***	-0.577 (1.289)	-15.169 (1.790)***
	σ	–	–	11.765 (3.508)***	23.666 (5.941)***
Chinese	μ	-19.008 (1.550)***	-9.674 (1.509)***	-19.848 (1.666)***	-6.049 (1.691)***
	σ	–	–	8.078 (4.173)	34.541 (6.544)***
S. Korean	μ	-9.510 (1.398)***	-19.361 (1.725)***	-10.412 (1.378)***	-17.774 (2.124)***
	σ	–	–	12.335 (3.850)***	54.771 (6.171)***
PHEV Fast-charge	μ	3.944 (1.330)***	7.615 (1.565)***	3.331 (1.335)	7.567 (1.653)***
	σ	–	–	8.882 (4.396)	20.119 (5.449)***
BEV Fast-charge	μ	3.343 (1.478)	6.662 (1.599)***	0.030 (1.821)	6.428 (1.668)***
	σ	–	–	26.237 (3.871)***	11.567 (5.360)
Operating Cost	μ	-1.598 (0.106)***	-3.214 (0.242)***	-1.626 (0.104)***	-3.467 (0.267)***
	σ	–	–	0.076 (0.247)	3.275 (0.968)***
Acceleration Time	μ	-1.172 (0.255)***	-4.651 (0.299)***	-1.269 (0.293)***	-4.878 (0.319)***
	σ	–	–	5.766 (0.880)***	3.359 (0.949)***
LL:		-3425.6	-6788.8	-3373.1	-6720.9
Null model LL:		-4360.5	-7487.3	-4360.6	-7487.3
AIC:		6883.3	13609.6	6808.3	13503.8
McFadden R2:		0.21	0.09	0.23	0.1
Adj. McFadden R2:		0.21	0.09	0.22	0.1
Num. of Obs:		5760	6720	5760	6720

typically have higher prices relative to other available conventional gasoline vehicles, these results suggest that the barriers to their adoption in the U.S. may be compounded by demographics. Those who can more easily afford an electrified vehicle are more opposed to them, and those who prefer them have lower incomes and may not be able to afford them.

In contrast to U.S. respondents, Chinese respondents who have higher incomes and higher education are *more* sensitive to operating cost, and those with larger households are less sensitive to price. While perhaps counter intuitive, it is important to note that operating cost and price are different types of costs. Some car buyers be more sensitive to operating cost to save money but less

to price because expensive cars are an important status symbol in Chinese culture. We also find no statistically significant income or age effects with vehicle technology. These results suggest that the higher income buyers who may be more able to afford electrified vehicles may also more highly value their operating cost savings, potentially further increasing their attractiveness. Finally, Chinese respondents with multiple vehicles and those who have access to home charging have statistically significantly positive effects for BEV technology, indicating that charging availability could be an important factor in preference towards pure-electric BEVs.

As might be expected, respondents in both countries who ranked appearing environmentally friendly as important have statistically significantly positive effects for all electrified vehicle technologies relative to conventional gasoline vehicles. For these respondents, they may be willing to pay a positive premium for an HEV, PHEV, or BEV in order to appear more environmentally friendly. Attitude towards being environmentally friendly is among the strongest factors correlated with preference towards any electrified vehicle type in both countries. However, U.S. and Chinese respondents differ on how they view electrified vehicles in terms of social status. U.S. respondents who rated their vehicle as being an important status symbol have statistically significantly positive effects for PHEVs and BEVs whereas Chinese respondents show the opposite effect. These results suggest that electrified vehicles may be viewed as a high-status symbol to U.S. car buyers but not so to Chinese car buyers.

3.5 Analysis

We use the estimated coefficients from model 2 to answer the primary research questions posed in the introduction.

3.5.1 U.S. and Chinese Willingness-to-Pay

RQ1: How do U.S. and Chinese preferences for EV technologies and attributes compare?

Since the coefficients from our models are in the WTP space, we can directly interpret the model coefficients as the amount respondents are willing to pay for incremental changes in each vehicle attribute independently of the other attributes. For example, when examining vehicle type we are comparing a difference in WTP for two vehicles that are identical in every way except for

powertrain type (e.g. a CV versus a HEV, with identical fuel economy, styling, operating cost, price, etc.). The only coefficient that cannot be so readily interpreted is the price coefficient, which is not a WTP estimate but rather an estimated constant that converts dollars to units of utility. It can equivalently be thought of as consumer sensitivity to price relative to the error term, with a larger coefficient signifying greater price sensitivity (more consistent choices). Past research has shown that respondent choices on hypothetical conjoint questions for high cost durables can be less sensitive to price relative to other attributes than when choices are made with real money in the marketplace [31], so we expect our estimates of WTP may potentially be inflated. Figure 3.2 below summarizes the mean WTP for each vehicle attribute in our survey. The error bars represent uncertainty in the mean.

U.S. respondent expected average WTP for BEV technology is \$10,000–\$20,000 lower than that for CV technology, depending on range—larger than what can be gained in fuel cost savings even if vehicle purchase prices were comparable. And fast charging capability does little to mitigate the drop in WTP. In contrast, expected average Chinese consumer WTP for BEV technology ranges from ~\$0 to \$10,000 lower than CVs, depending on range, with fast charging capability increasing expected average WTP by \$6,400. We also find a large and significant WTP heterogeneity for the lower range BEV₇₅ in China (standard deviation of \$19,000), which becomes substantially smaller with increased range (standard deviation of \$7,000 for a BEV₁₅₀). Such large standard deviations could suggest bimodal preferences. Average WTP for other vehicle technologies are not statistically significantly different from CV in either country, although the expected value of WTP for HEVs is higher in China (~\$5,000), and expected WTP for PHEVs is higher in the US (~\$3,200–\$3,300 for PHEV₂₀ and PHEV₄₀).

Parameters for operating cost and acceleration time are both significant and robust to model specification, with consistent signs and orders of magnitude across all models. On average, Chinese respondents are willing to pay nearly double the premiums U.S. respondents are willing to pay for a decrease in operating costs (\$3,000 and \$1,600 per \$0.01/mile-reduced, respectively), and Chinese respondents are willing to pay nearly three times what U.S. respondents are for a decrease in the 0 to 60 mph acceleration time (\$5,000 and \$1,200 per 1 second decrease, respectively), likely in part due to vehicles in the Chinese market having substantially lower acceleration capabilities than those in the U.S. market. These results hold across all models.

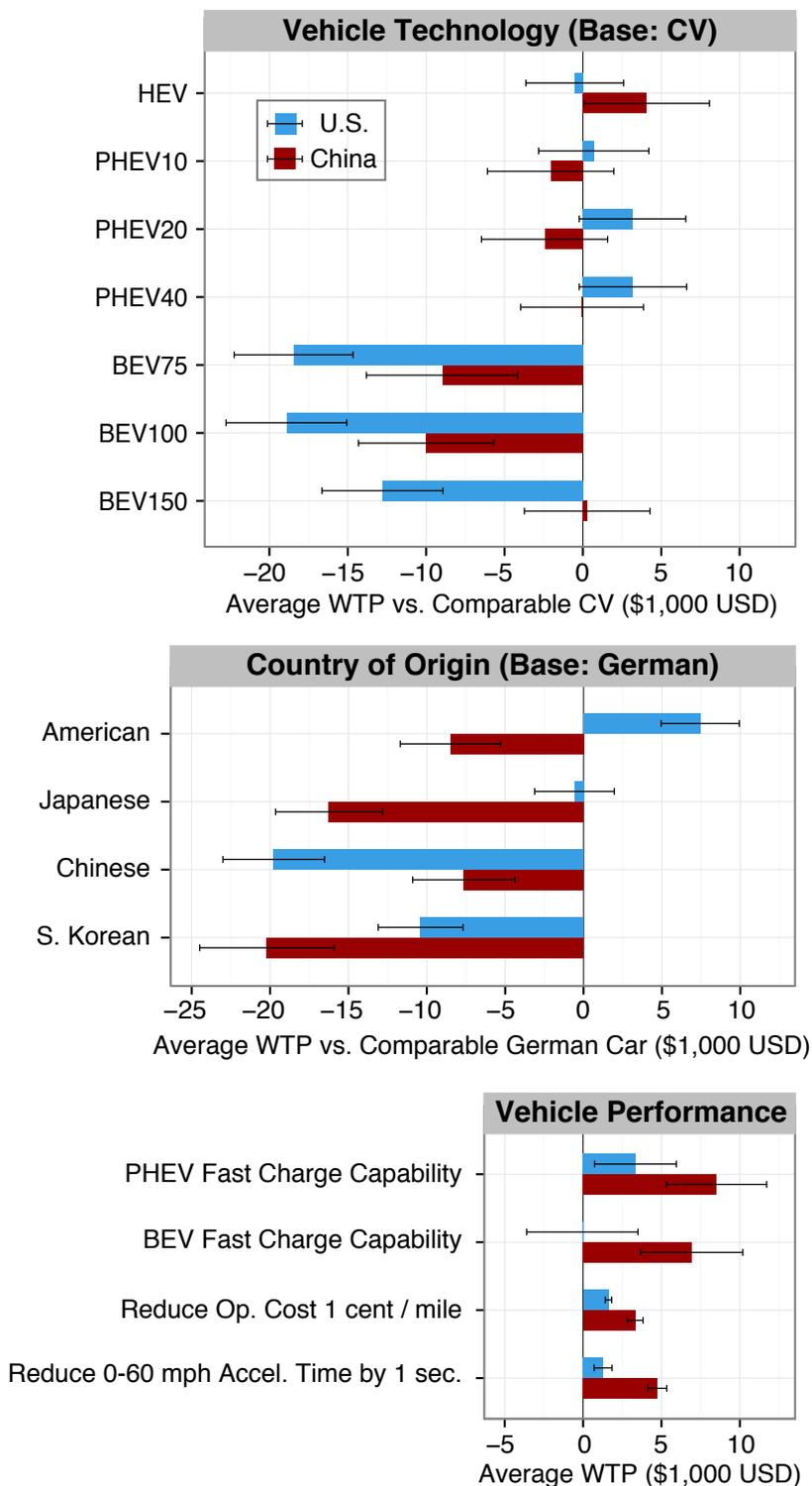


Figure 3.2: Mean willingness-to-pay to change each vehicle attribute independently of other attributes in China and the U.S. (Model 2). WTP for vehicle technology indicates preference for the technology alone, independent of any expected influence of that technology on operation cost, performance, or other attributes. Error bars show a 95% confidence interval for the estimated population mean.

Finally, all brand effects are significant with large magnitudes and large, statistically significant differences between the two countries. The brand ranking from most preferred to least preferred, *ceteris paribus*, for the U.S. is: American, Japanese, German, S. Korean, and Chinese. For China the brand ranking is: German, Chinese, American, Japanese, and S. Korean. We estimate that on average Chinese respondents are willing to pay as much as \$18,000 and U.S. respondents as much as \$27,000 to move from equivalent vehicles of the least preferred to the most preferred brands. We find large standard deviations in WTP for brand in both countries, suggesting large heterogeneity in brand preference (as may be expected for passenger vehicles).

3.5.2 Plug-in Vehicle Competition Without Subsidies

RQ2: How would plug-in vehicles compete against their gasoline counterparts in each country without subsidies?

Consumer willingness to adopt plug-in vehicles will depend on the mix of attributes manufacturers are able to offer in a single vehicle (technology type, range, acceleration, operation cost, price, etc.)—not just the vehicle type. To examine the implications of the model coefficients for consumer WTP towards combinations of attributes offered in today’s plug-in vehicles, we use model 2 to simulate choices among select plug-in vehicles currently available and their gasoline counterparts. Each simulation is a pairwise comparison of a plug-in vehicle versus its gasoline counterpart as if they were the only two vehicles available for all car buyers. The conjoint model is not appropriate for making full market forecasts among all vehicles in the marketplace because key attributes that vary across vehicles in the marketplace and drive consumer choice (such as aesthetics, size, etc.) were held constant in the conjoint study. However, the model can be applied to compare vehicles that have identical bodies and differ only in powertrain characteristics captured by the conjoint attributes. Future work may consider joint models using stated and revealed preference data to simulate the entire market [47, 56]. We run each simulation using 2012 vehicle attributes (as this is the year our data was collected) in different subsidy environments. The attribute values used in the simulations are listed in Appendix A.2. Figure 3.3 summarizes the simulation results for no subsidy.

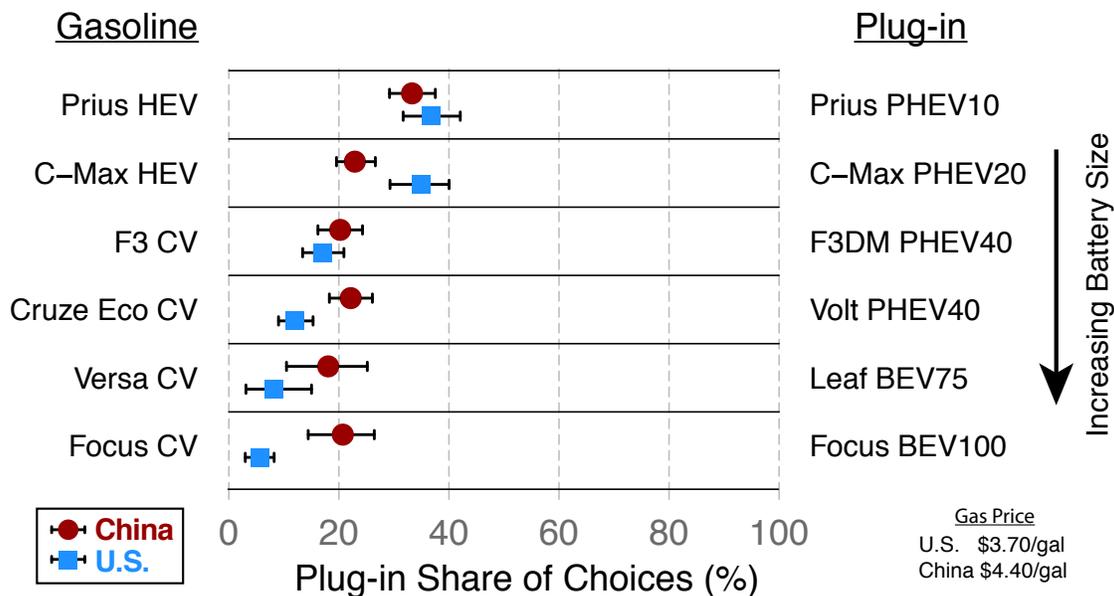


Figure 3.3: Predicted share of respondent choices for select plug-in vehicles and their gasoline counterparts in 2012 vehicle attributes. Vehicle attributes used in these simulations are in detailed in Appendix A.2.

We chose vehicles for which the body and general appearance are similar between different vehicle types (such as the Ford Focus CV and Ford Focus BEV₇₆ (modeled as a BEV₇₅), since this mimics how our survey was presented, and since choice models can predict share when all attributes excluded from the model (including aesthetics) are identical across vehicle alternatives or have a negligible effect on choice. It is important to note that these share estimates reflect the expected outcome if every survey respondent selects one vehicle from the two vehicle options available in each case. Since the set of consumers who would consider the two vehicle models in practice is not a random subset of the respondents (and for other reasons such as limited availability of different vehicle models, advertising, incentives, etc.), the observed share in the marketplace will differ. Most of these vehicles are not yet available for sale in China and are only available in relatively small numbers in the U.S. In addition, early adopters form the majority of current plug-in vehicle sales; since our sample is of mainstream car buyers, these simulations allow us to examine larger, mainstream preferences for these technologies.

We make comparisons between six pairs of plug-in and gasoline vehicles: two comparing PHEVs to HEVs, two comparing PHEVs to CVs, and two comparing BEVs to CVs. Without any subsidies, we find that the HEVs are preferred to the PHEVs in both countries. The CVs are also preferred

over their PHEV counterparts in both countries to an even larger degree than the HEVs. The only result with a significant difference between the U.S. and China is for the BEV simulations. We find that BEVs compete poorly against their CV counterparts in the U.S. but compete substantially better in China, reaching approximately 20% share of choices without subsidies, similar to how the PHEVs compete against their CV counterparts.

3.5.3 Plug-in Vehicle Competition With Subsidies

RQ3: How do subsidies influence the competitiveness of plug-in vehicles vs. their gasoline counterparts?

To examine how federal subsidies might influence plug-in vehicle competitiveness, we run simulations of the same pairs of plug-in and gasoline vehicles under varying subsidy environments, scaling from \$0 to \$20,000 per vehicle. Today's national subsidies are summarized in Appendix A.6. In both the U.S. and in China subsidies vary with battery capacity, providing lower subsidies for small-battery low-range PHEVs and larger subsidies for larger-battery longer-range PHEVs and BEVs. Our sensitivity study covers roughly twice the range of national subsidies observed today. We treat subsidies as though they only affect the price observed by the consumer, although in practice consumer knowledge that a vehicle is being subsidized may influence consumer adoption in other ways for which we lack data, and subsidies in the form of tax breaks may not be realized at full value for all consumers and/or valued on a dollar-per-dollar basis by all consumers. We plot the results of the plug-in vehicle share of choices versus the subsidy in Figure 3.4. The shaded region represents a 95% confidence interval based on uncertainty in the parameters and was calculated using 10,000 simulated draws from the model described in equation 3.3.

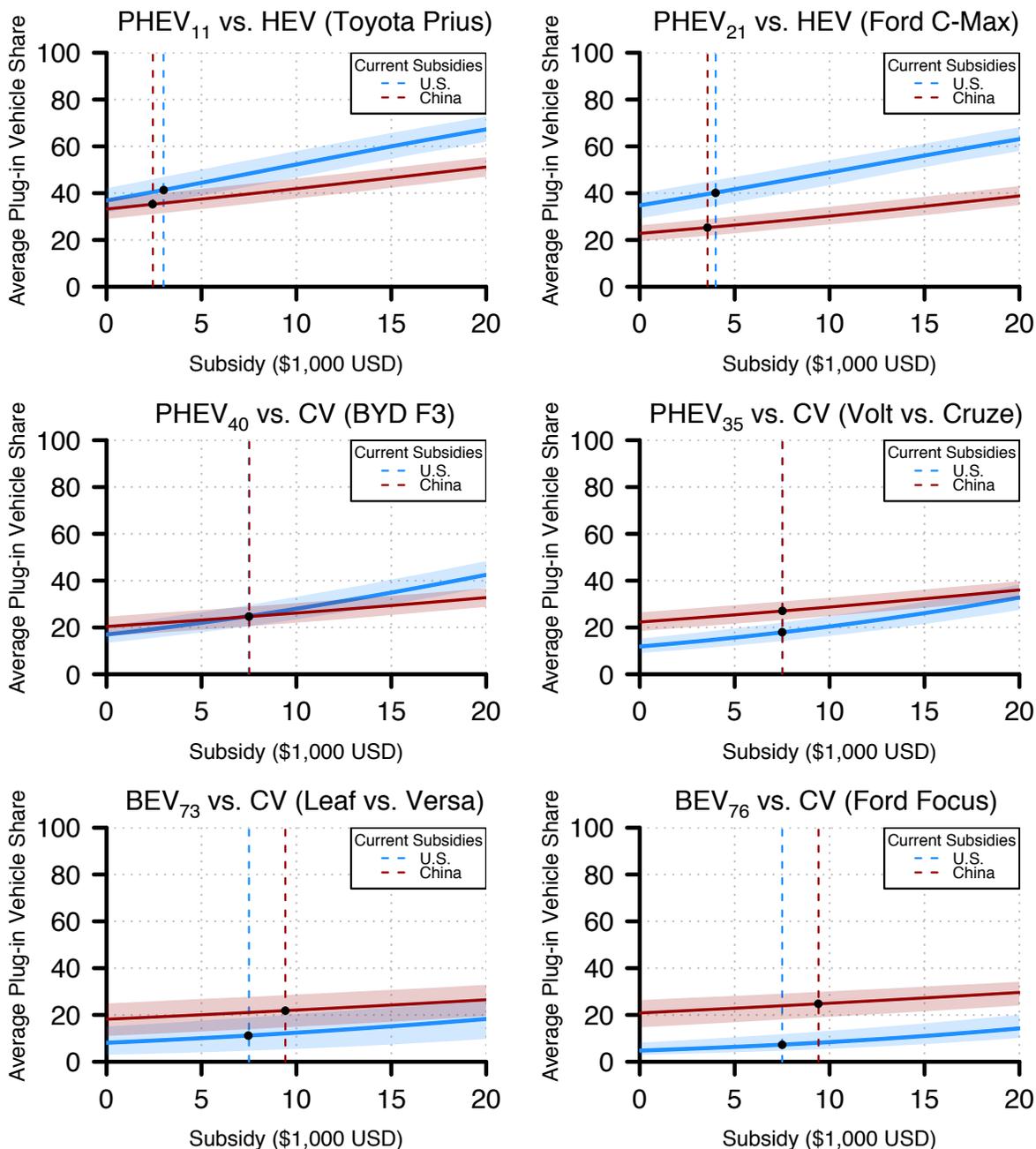


Figure 3.4: Simulated share of respondent choices for select plug-in vehicles and their gasoline counterparts, illustrating how share changes with increasing plug-in vehicle subsidies. The vertical lines indicate the current plug-in vehicle subsidy in each country.

Results suggest that share of BEVs is higher in China than the U.S. and that share of low-range PHEVs is likely higher in the U.S. than in China whenever the two countries have comparable subsidies. Results are inconclusive for the mid-range PHEV cases as shares are similar between the two countries for the BYD case but higher in China for the Chevrolet case (likely a result of the

high price of the *Volt* relative to the *Cruze Eco*). To achieve a 50% share of plug-in vehicles vs. their gasoline counterparts (indicating no net preference for one over the other in the population), the low-range PHEVs would require a U.S. subsidy of about \$9,000 and a Chinese subsidy of \$18,000 or more. In contrast, the larger battery PHEVs and BEVs would require subsidies exceeding \$20,000 in both countries to achieve a 50% share of choices. Under current subsidies, low-range PHEVs could achieve a 41-44% share in the U.S. and a 32-36% share in China vs. their respective gasoline counterparts, while larger-battery PHEVs could achieve only a 25-33% share in the U.S. and a 26-35% share in China vs. their respective gasoline counterparts. In contrast, the current subsidies for BEVs have substantially different impacts on share between China and the U.S., achieving a 24-25% share in China while only a 7-12% share in the U.S. vs. their respective gasoline counterparts.

3.6 Limitations

Both the U.S. and China have a range of policies in addition to federal subsidies that influence adoption of electrified vehicles. For example, in the U.S., state level subsidies for plug-in vehicles as high as \$7,500 per vehicle are added to federal subsidies [57]; state mandates like California’s zero-emission vehicle (ZEV) program force automakers to sell specific technologies, such as electrified vehicles—often at a loss [58]; perks like high-occupancy vehicle (HOV) lane access for plug-in vehicles hold high value for some consumers [59]; and government fleet purchases influence sales. In Beijing, BEV buyers are exempt from going through the city’s lottery system to obtain a license plate (only one out of 77 applicants were awarded plates in February, 2013), and local subsidies reach a maximum of ¥120,000 RMB (~\$19,600 USD) [60]. For tractability, we do not attempt to assess the effect of local and non-monetary policies on electrified vehicle adoption.

Additionally, while our choice-based conjoint study was designed to mitigate bias, consumer decisions in practice may deviate from reported choices in a hypothetical survey environment. As previously noted, it has been observed that respondent choices on hypothetical conjoint questions for high cost durables can be less sensitive to price than choices made with real money in the marketplace [31], so we expect estimates of WTP to potentially be somewhat inflated. Further, we use point estimates for fuel economy, gas price, and vehicle price that, in practice, may vary from consumer to consumer (e.g.: city vs. highway driving [61], gas price regional or temporal

fluctuations, and vehicle purchase transaction prices via dealer negotiation and financing).

More generally, research has shown that consumer choice often does not follow neoclassical economic assumptions of utility maximization, especially when consumer learning about new technologies is involved. For example, Turrentine and Kurani (2007) provide a useful critique of the utility maximization framework for vehicle fuel economy and offer alternative approaches rooted in anthropological study; in a study of semi-structured interviews of 57 households in California, they found that consumer decisions about fuel economy were more heavily influenced by emotion rather than analysis and that car buyers do not think about fuel economy in terms of payback periods, WTP, or other constructs based on the assumption of economic rationality [62]. Furthermore, similar research has shown that sometimes buyers of HEVs make functional compromises in order to gain the symbolic benefits associated with driving a vehicle that is viewed as more environmentally friendly [63]. Other research has shown that these effects can be further magnified through a “neighbor effect,” where “a new technology becomes more desirable as its adoption becomes more widespread in the market” [47]. In China, where owning a vehicle is such a strong social status symbol, such effects could be influential in driving consumer choice.

It is difficult to separate consumer responses on our survey from the current social and policy environments that may influence perception of and preferences for electrified vehicles. Further, future vehicles, both conventional and electrified, will have different attributes and prices from today’s vehicles. In comparing currently available plug-in vehicles to their current gasoline counterparts, we do not aim to predict current market behavior, especially since current adoption trends are driven by early adopters [64] and our samples are of mainstream consumers. Our share simulations are based on the situation where all consumers consider only the plug-in vehicle vs. its gasoline counterpart. In addition, factors other than consumer preferences play a major role in influencing adoption, including policies such as California’s ZEV policy (increasing Nissan *Leaf* sales in California [58]), and supply constraints. China in particular faces large supply constraints, with currently no commercially available BEVs for sale to private owners, and only a small set of HEV models available.⁹

Finally, while our consumer preference results suggest the potential for greater BEV adoption

⁹Although this was true during the time of data collection (2012), today (2016) multiple automakers offer plug-in vehicles in China.

in China, other factors, such as the joint venture regulation on foreign automakers, intellectual property rights protection in China, firm experience with each technology, and consumer access to off-street parking and authorization for charger installation [65], complicate future adoption patterns.

3.7 Conclusions

Vehicle electrification is one particularly promising option to reduce world wide air emissions and oil consumption. Different vehicle electrification technologies have difference consequences for air emissions (and thus local and global health) and oil consumption (and thus national security): HEVs continue to rely on gasoline, PHEVs use grid electricity to displace additional gasoline, and BEVs displace gasoline entirely. Air emissions implications for plug-in vehicles (PHEVs and BEVs) depend on battery manufacturing and the mix of sources used to generate electricity.

Vehicle technology adoption in China and the United States is influenced by consumer preferences and public policy. We model consumer preferences for conventional, hybrid electric, plug-in hybrid electric, and battery electric vehicle technologies in China and the U.S. using data from choice-based conjoint surveys fielded in both countries. Results suggest that the expected average U.S. consumer WTP for BEV technology is \$10,000–\$20,000 lower than equivalent conventional technology (depending on range, fast charging availability, and model specification) *ceteris paribus* (given the same body, brand, performance, and operating cost). In contrast, average Chinese consumer WTP for BEV technology is within \$10,000 of equivalent conventional vehicles and in some cases (e.g.: with sufficient range and fast charging capability) is larger.

To understand the competitiveness of the combined bundle of attributes realized with today’s technology, we apply WTP for vehicle type, price, brand, operating cost, and acceleration to attributes of plug-in vehicles available today and their gasoline counterparts. We find that in China, BEVs and mid-range PHEVs both compete comparably with their respective gasoline counterparts, while in the U.S., mid-range PHEVs compete more strongly than BEVs against their respective gasoline counterparts. Low-range PHEVs compete most strongly against their gasoline counterparts in both countries. These patterns hold in both countries with or without the 2012-2013 national subsidies, which favor large-battery PHEVs and BEVs over low-range PHEVs in both countries.

Further, these patterns hold in both countries even if all subsidies were doubled.

Overall, our results suggest that Chinese respondents are more receptive to BEVs than American respondents regardless of subsidies. The Chinese car market has several key distinctions that might support BEV adoption. First, approximately two-thirds of Chinese car buyers are first-time buyers who typically have less experience with both gasoline and plug-in vehicle technology and who may not have established expectations for the ability to take long trips. In addition, many Chinese consumers have experience with electric bicycles, so the culture of plugging in a vehicle and driving short distances is well established. Furthermore, China has a major intercity train system, providing inexpensive and reliable travel between cities. This alternative allows consumers to mode shift to trains during longer trips, an alternative less accessible in the U.S. These preferences, which support the adoption of BEVs, have clear national security benefits for China.

While our consumer preference estimates point to greater potential for mainstream adoption of BEVs in China than the U.S., the electricity grid in China is more emissions-intensive than that of the U.S., and a shift to BEVs might result in increased air pollution and/or GHG emissions, depending on the emissions intensity of the vehicles displaced, marginal grid emissions factors in the regions where plug-in vehicles are adopted, and driving patterns. In contrast, today's HEVs, which reduce oil consumption and emissions, have higher near term adoption potential in both countries and may therefore offer more total emissions and oil displacement benefits in the near term, given today's electricity grid, technology attributes, and consumer preferences.

Given that China is now the largest consumer and producer of automobiles worldwide, the trends in China's market and the strategies of automakers and the government in China have the potential to change the economic incentives for emerging technology development worldwide. Even though EV adoption in China might increase local emissions, global emissions from automobiles could nevertheless plausibly decrease as a result of increased development and adoption of EV technology worldwide.

Chapter 4

When Should We Pool Revealed and Stated Preference Data? Assessing Endogeneity and Context

4.1 Study Overview

Chapter 3 used a quantitative utility model to measure and compare consumer preferences for electrified vehicle technologies in the U.S. and China. A known critique is that the results are based on survey data, which may be inconsistent with consumer choice behavior in the marketplace. In this chapter, we discuss an existing method for estimating a pooled model that uses both survey and actual market sales data. While the original goal was to improve the results from Chapter 3, our research focus shifted instead to important concerns with the modeling method. Specifically, we explore the benefits of pooling when there are endogenous parameters in the market data (a commonly cited source of parameter bias in market choice data) and when consumer response to attributes is different in the survey context versus the market for which we want to recover parameters. Results suggest that the presence of these factors can greatly affect pooled model parameters. We show that when endogeneity is present in the market data, the likelihood ratio test is neither necessary nor sufficient to determine whether survey and market data should be pooled.

The study presented in this chapter is based on a working paper. The use of first person plural includes coauthors Elea Feit and Jeremy Michalek.

We provide new guidelines for understanding under what conditions pooling data sources may or may not be advisable for accurately estimating true market preference parameters, including consideration of the context and conditions under which the data were generated as well as the relative balance of information between data sources.

4.2 Introduction

Quantitative modeling to predict choice is an established area of research in econometrics, psychology, and marketing [30, 32]. The general approach uses a utility model to estimate parameters based on data from observed consumer choices. Although previously developed modeling techniques take many forms, the data for such models typically comes from one of two sources: “Revealed Preference” (RP) data and “Stated Preference” (SP) data. RP data comes from actual purchases made by consumers in the marketplace, and SP data comes from controlled survey experiments where respondents rate, rank, or make choices from a set of hypothetical products controlled by the researcher [32]. The strengths and weaknesses of each data source are summarized in Table 4.1.

Table 4.1: Comparison of stated and revealed preference data

	Stated Preference (SP)	Revealed Preference (RP)
Strengths	<ul style="list-style-type: none"> • Can include hypothetical products • Controlled 	<ul style="list-style-type: none"> • Reflects choices from real market
Weaknesses	<ul style="list-style-type: none"> • Potential difference in survey vs. market choice behavior 	<ul style="list-style-type: none"> • Potential for endogenous variables • Low attribute variation • Measurement error • Multicollinearity among explanatory variables • Missing information about consideration sets • Limited to currently available products • Product availability

RP data reflects real purchases where money is exchanged for goods and/or services. As a result, model parameters estimated using RP data are generally believed to reflect consumers’ preferences in the real-world market context. However, RP data is susceptible to a number of

modeling concerns that could result in biased parameter estimates. In particular, endogeneity is a common concern and occurs when an observed variable is correlated with the error term. For example, price could be endogenous if an unobserved attribute that influences choice (e.g. the “style” of a vehicle) also influences the price that manufacturers set [37]. In particular, for the case of automobiles it is virtually guaranteed that any model posed with RP data will be misspecified and omit difficult-to-observe and/or difficult-to-model attributes that play a role in driving consumer purchase choices. Guevara (2015) provides a review of multiple examples of endogeneity in past RP data studies, including endogeneity in public transportation models, housing choice models, and interurban mode choice models [66]. In response, a number of past studies have developed methods to overcome endogeneity, including the use of proxy variables [67,68], the two-step control function [69,70], the integration of latent variables [71], the multiple indicator solution [72], and the BLP approach [37]. Other concerns with RP data include measurement error (particularly in measuring the attributes and prices faced by decision makers in the market) and multicollinearity (e.g. *price* and *luxury* are typically positively correlated). Thus while RP data has the face validity of reflecting real market choices, the modeler remains uncertain whether or not the estimated parameters are unbiased estimates of the true parameters that generated the data.

In contrast, SP data is collected in controlled survey experiments, allowing the researcher to avoid many of the concerns that arise in RP data by controlling the observable attributes, designing the survey to avoid attribute correlations, and avoiding the presence of attributes observable to the consumer that are not observed by the modeler. In addition, SP data can provide information about consumer preferences for products or attributes that are not yet available in the market. However, SP data is generated in a different context from RP data, and the researcher often does not know the degree to which consumer behavior in a particular survey context will match purchase behavior in the market context of interest. Carson and Groves (2007) illustrate that different incentives provided by particular response formats on surveys can induce “strategic behavior” in respondents, and unless the collected information is “incentive compatible” with the real-world incentives, respondents may (intentionally or not) choose not to reveal their true preferences [73]. Ding et al. (2005) show a similar result in which models estimated from “incentive-aligned” choices (where respondents were required to actually purchase one of their chosen conjoint profiles) made predictions that were more consistent with observed market choices [74]. Thus while there are fewer

econometric challenges to recovering true parameters in a survey context, the modeler typically remains uncertain about the degree to which those parameters are comparable to the corresponding parameters in the market context.

In short, RP and SP data often have opposing uncertainties: in the RP (SP) context, modelers are often more (less) certain that the data reflect true market preferences but less (more) certain whether parameters estimated from those data are biased. Whether or not any of these issues are cause for concern in any specific data set depends on the context of the data (how they were generated and collected), and the degree of concern about the potential presence of these issues is typically determined subjectively by the modeler in the absence of definitive empirical evidence. In some cases, a modeler using RP data may have reason to believe that all important choice-driving attributes have been fully and accurately observed, reducing the potential for an omitted or poorly-measured variable to induce an endogeneity. In other cases, important attributes may be unobserved or difficult to quantify (e.g. *aesthetics*) and the modeler must consider whether those attributes are correlated with other observed attributes in the model or how (if possible) to represent them in the model. Likewise, it is difficult to determine whether or not the choices made in a set of SP data are similar to how those consumers would make choices in real markets. The modeler must make decisions as to whether or not any estimated parameters might be biased or different from the real market context based on his or her modeling experience and knowledge of the data. Because these important concerns are based on the modeler's beliefs, there is little evidence of how these problems will play out in model estimation.

In comparing the characteristics of RP and SP data, previous researchers have recognized the opportunity to utilize both through pooling with the goals of mitigating their relative weaknesses and benefiting from their relative strengths. To examine if pooling is justifiable, the prior literature has used visual and statistical tests such as the likelihood ratio test [75] to consider whether or not parameters from RP and SP contexts are comparable. Perhaps surprisingly, the previous literature has not considered the effect of endogeneity in pooled models despite its prevalence in RP data. In this study, we use a synthetic data experiment to investigate the conditions under which pooling succeeds in recovering true model parameters in the presence of endogeneity in the RP data and differences between the RP and SP contexts.

4.3 Literature on Pooled RP-SP Models

Pooled models¹ make the assumption that preferences for attributes common to both RP and SP data sets can be modeled with common parameters. Conceptually, if β^R and β^S are vectors of parameters for attributes common to RP and SP data sources, then the pooled model places a restriction where these attributes are modeled with the same vector of parameters, β . Attributes that are only observed in one data set are modeled with data source-specific vectors of parameters given by γ^R and γ^S . Figure 4.1 provides a conceptual diagram of the RP, SP, and pooled models (we describe the model in detail in section 4.4).

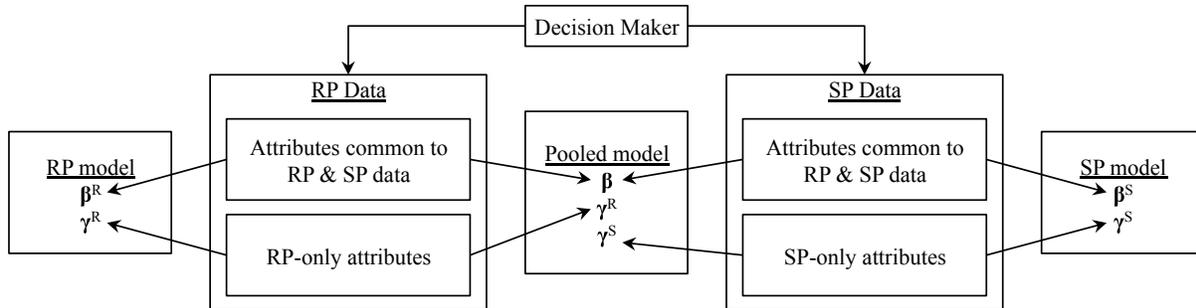


Figure 4.1: Conceptual diagram for the RP, SP, and pooled models. Superscripts “R” and “S” refer to RP and SP data sources, and the arrows indicate which data informs parameter estimates. Parameters in β are for common attributes while those in γ^R and γ^S are for attributes specific to the RP and SP data sources.

The pooled RP-SP model was originally developed by Morikawa (1989) [77] and has since been used in numerous studies to overcome some of the limitations of RP data, such as including information on attributes or alternatives that do not exist in RP data [46,47,78–83] and improving statistical properties of the data by adding variation to highly collinear attributes in RP data [31,46,56,84–87]. Some studies also argue that RP data “grounds” the SP data in reality [31,46,47,56,76,79,88–91]. Table 4.2 summarizes the literature on pooled RP-SP models.

A common narrative across many past studies is that pooled models “benefit from the relative strengths and mitigate the relative weaknesses” of each data source [46,47,76,78–81,83,89–92]. Some studies go even further and claim that pooled RP-SP models generate more “accurate” parameter estimates than either RP or SP models [56,79,80,86], while others claim that pooling reduces the

¹We focus on the pooled model since pooled model parameters are informed by both data sets. While the sequential model provides another approach for using RP and SP data, attribute coefficients are only informed by the SP data while the RP data is used to calibrate predictions to actual market shares [76].

bias that would result when estimating the model from a single data source [78, 80, 82] without specifying the source of the bias.

Nonetheless, the literature has recognized that pooling may not be warranted for some RP/SP data sets. One way to detect if pooling is reasonable is to plot the coefficient estimates for the common attributes from an RP-only model against those from an SP-only model. If the two models share the same coefficient for common attributes, the points should fall along a line (up to sampling error).² Swait and Louviere (1993) propose using a likelihood ratio (LR) test where the null hypothesis is that the coefficients are the same in the RP and SP data (once scale differences are accounted for in preference space models), so the test accepts pooling of RP and SP data unless there is sufficient evidence to *reject* pooling [75]. Numerous past studies have used this test to justify pooling assumptions [46, 56, 78, 79, 81, 84, 85, 87, 88].

Although the idea that pooled RP-SP models will reduce parameter bias is intuitively appealing, our literature review of 23 pooled RP-SP studies finds only one study [93] that considers the accuracy of parameter estimates in the presence of endogeneity, and results were inconclusive due to limitations in the data used in that study. While pooled models have been shown to achieve better predictive performance on within-sample or hold-out prediction tests in several applications [31, 46, 47, 76, 81, 83, 85, 87, 92], it is well-known that predictive performance is not indicative of parameter accuracy [94]. Prior papers on pooling implicitly assume away endogeneity in the RP data and do not attempt to assess endogeneity bias. Since the true preference parameters in real data sets cannot be known, we use a synthetic data experiment to explore the outcomes of pooled models under different conditions of endogeneity in the RP data and differences between the RP and SP contexts.

²For models estimated in the preference space, the slope of this line may not be 1, due to differences in scale between the RP and SP data sets.

Table 4.2: Summary of previous literature on pooled RP-SP models

Study	Pooling Motivation	Conclusions
Adamowicz et al., 1994 [84]	Improve RP collinearity; include non-existing attributes	SP improves “quality” of RP estimates; RP collinearity reduced; attribute ranges not presently available analyzed
Adamowicz et al. 1997 [85]	Improve RP collinearity; include non-existing attributes; Compare perceived vs. objective attributes	Respondent decisions based on attribute perceptions rather than objective value
Axsen et al., 2009 [47]	Improve RP collinearity; include non-existing attributes; RP adds realism	Greater RP influence, better on statistical measures; greater SP influence, more realistic WTP
Ben-Akiva and Morikawa, 1990 [78]	Include non-existing attributes; RP corrects SP biases	“...combined estimation...can be used to exploit their advantages. In particular, the combined estimation explicitly identifies the differences between the RP and SP data generating processes.”
Bhat and Castelar, 2002 [88]	Add flexible substitution patterns (MXL model) and state dependency in joint models	Suggest “using SP experiments as the main data source for analysis and supplementing with small samples of RP data for anchoring with actual market activity.”
Birol et al., 2006 [79]	Improve RP collinearity; include non-existing attributes	“...combined estimation enables more robust and efficient identification”
Börjesson, 2008 [92]	Improve RP collinearity; SP data might be less trustworthy for trip timing	Different scheduling disutility across RP and SP choices imply temporal differences in RP and SP choice situations
Brownstone et al., 2000 [46]	Improve RP collinearity; include non-existing attributes	“RP data...critical for obtaining realistic body-type choice and scaling information...SP data are critical for obtaining information about attributes not available in the marketplace, but pure SP models...give implausible forecasts.”
Disanayake and Morikawa, 2003 [80]	Include non-existing attributes; “to improve the accuracy of parameter estimates while exploiting the advantages of both RP and SP [data]”	“It has been clearly observed that the combined estimation of RP and SP data in travel demand modeling is an effective technique for expressing complex travel behavior and forecasting the travel demand for new transport services.”

Feit et al., 2010 [31]	Adjusting conjoint parameters to be more consistent with observed market choices	Joint model benefits from well-conditioned conjoint data and predicts market data much better than conjoint model
Hensher and Bradley, 1993 [81]	Introduces the use of a nested model to estimate scale differences (the FIML procedure)	“...additional information from SP data gives the RP model increased richness and sensitivity for prediction. The use of SP data to estimate alternative-specific constants for new products is a major contribution to enriching an RP application in the presence of a new alternative.”
Hensher et al., 1999 [56]	Surveys past studies on joint RP-SP approaches, in particular different error structures.	“...we are able to utilise the well-behaved SP design matrix to correct sign and collinearity problems in the RP data...we are also able to obtain more robust parameter estimates...The availability of the RP data...contributes a ‘real-world flavour’ to the joint model by establishing alternative-specific constants that reflect population characteristics.”
Hensher et al., 2008 [95]	“This paper promotes the replacement of the NL ‘trick’ method with an error components model that can accommodate correlated observations as well as reveal the relevant scale parameter for subsets of alternatives.”	“The nested logit approach is...not capable of accounting for the potential correlation induced through repeated observations on one or more pooled data sets.”
Huang et al., 1997 [90]	“The purpose of this paper is to demonstrate the conditions for consistently combining revealed (trip demands) and stated (contingent valuation) data for an improvement in environmental quality.”	“Our results show that revealed and stated data should not be combined under the same assumed preference structure unless the two decisions imply the same change in behavior induced by the quality change.”
Mark and Swait, 2004 [87]	Improve RP collinearity; include non-existing attributes; Improve the ability to evaluate choice of health care products	“This paper illustrates how SP data (hypothetical prescription choices)...and RP data...(perceived medication attributes and reported medication usage) can be employed to understand the factors influencing physician prescribing decisions.”
Mark and Swait, 2008 [91]	Improve RP collinearity; include non-existing attributes; “our interest will be in improved prediction of some form of market behaviour.”	“Data enrichment allows one to capitalise on the realism of actual health care choices with the favourable statistical characteristics of hypothetical choices”
Morikawa, 1994 [96]	Parameter efficiency, “bias correction,” and identification of new attributes	Develops a method for correcting state dependence and serial correlation in the RP / SP combined estimation method.

Poly-doropoulou and Ben-Akiva, 2001 [82]	“[pooling]...provides more reliable estimation results because the RP data...counteract the SP-related biases, and it provides the capability to estimate the demand for new mass transit technologies.”	“The results demonstrate the...advantages of simultaneously estimating models with different data sets and sharing common coefficients.”
Román et al., 2007 [97]	RP data for actual travel data, SP data for non-existing alternatives	“results...cast doubts on the competition that HSTs can exert in markets characterized by high-frequency air services.”
Small et al., 2005 [98]	Improve RP collinearity; include non-existing attributes; improve statistically precision	“...we are able to measure properties of travel preferences that have eluded other studies. We find that travel time and its predictability are highly valued by motorists and that there is significant heterogeneity in these values.”
Swait et al., 1994 [76]	New modeling approach (sequential) to “exploit the strengths and avoiding the weaknesses of each data source.”	RP data ground model in reality (with ASCs), SP data help reduce statistical problems in RP data; “...choice forecasts of the Sequential model are practically indistinguishable from those of the RP-only model, and in quite a few cases actually improved over the performance of the latter.”
Swait and Andrews, 2003, [83]	“The fact that different choice data sources have diverse strengths and weaknesses suggests it might be possible to pool multiple sources to achieve improved models, due to offsetting advantages and disadvantages.”	Pooled model performed better on holdout predictions even though the LR test rejected parameter homogeneity.
von Haefen and Phaneuf, 2008 [93]	Improve RP collinearity; include non-existing attributes; improve statistically precision; correct for endogenous RP parameters	“...our combined RP/SP approach to identifying preference parameters in the presence of unobserved determinants of choice represents a feasible and in many ways attractive alternative to RP approaches.”

4.4 The Data Generating Process

4.4.1 The Random Utility Model

The random utility model is an established framework for estimating statistical models based on data from observed consumer choices [30,32]. The basic assumption is that consumers make product choices based on their individual utility for each product, u , which can be represented as a function of the deterministic attributes of the product, $v = f(\mathbf{x})$, and the unobserved attributes, ε , which is modeled as a random variable such that $u = v + \varepsilon$. It is also often assumed that the deterministic utility to consumer n for alternative j on choice occasion t , v_{njt} , is linear in parameters and can be represented as $v_{njt} = \boldsymbol{\beta}'_n \mathbf{x}_{jt}$. Since our focus is on parameter biases, we simplify the discussion by focusing on homogeneous models that assume $\boldsymbol{\beta}_n = \boldsymbol{\beta} \quad \forall n \in N$, although we expect these findings would extend to heterogeneous choice models.

An important aspect of the random utility model is that the absolute level of utility is irrelevant; model predictions only depend on *differences* in utility, meaning parameter values only have relative rather than absolute value. For identification, one parameter must be set to a fixed value that serves as a reference point. The resulting coefficient estimates will have different interpretations depending on which parameter is fixed. Two common choices are the *scale* parameter and the *price* parameter, resulting in the “preference” space and “willingness-to-pay” (WTP) space models, respectively [55]. To illustrate the difference between these two spaces, consider the following utility model:

$$u_{jt} = \lambda (\alpha p_{jt} + \boldsymbol{\beta}' \mathbf{x}_{jt}) + \varepsilon_{jt} \quad (4.1)$$

Here α and $\boldsymbol{\beta}$ are parameters for price, p , and non-price attributes, \mathbf{x} , and the error term ε has a relative scale of $1/\lambda$. Setting the *scale* parameter to $\lambda = 1$ results in the preference space model given by

$$u_{jt} = \alpha p_{jt} + \boldsymbol{\beta}' \mathbf{x}_{jt} + \varepsilon_{jt} \quad (4.2)$$

Here the parameters α and $\boldsymbol{\beta}$ represent the marginal utility derived from changes in attributes p and \mathbf{x} , and the scale of utility is relative to the scale of the random variable ε , which is typically

modeled with an assumed distribution. In contrast, setting the *price* parameter to $\alpha = 1$ results in the WTP space model given by

$$u_{jt} = \lambda (p_{jt} + \boldsymbol{\beta}'\mathbf{x}_{jt}) + \varepsilon_{jt} \quad (4.3)$$

Here the parameters in $\boldsymbol{\beta}$ represent the relative importance of each attribute \mathbf{x} versus p (the WTP for changes in \mathbf{x}), and λ represents the size of the effect of observed attributes on choice compared to the size of the assumed distribution of the random error term ε .³ Table 4.3 summarizes the parameter interpretations in the two spaces.

Table 4.3: Utility model effects in preference vs. WTP spaces

Effect	Preference Space	WTP Space
Relative importance of \mathbf{x} vs. p	$\boldsymbol{\beta}/\alpha$	$\boldsymbol{\beta}$
Relative importance of p vs. standardized noise	α	λ
Relative importance of \mathbf{x} vs. standardized noise	$\boldsymbol{\beta}$	$\boldsymbol{\beta}\lambda$

With a large enough sample size, the two approaches are equivalent in that coefficients estimated in one space can be calculated from those estimated in the other space.⁴ Since preference space model coefficients that have units of *utility* are difficult to interpret, researchers often compute WTP in units of currency from them post-hoc. In contrast, WTP space models have the convenient advantage of directly estimating WTP without the need for post-hoc computations. In addition, since the WTP space coefficients in $\boldsymbol{\beta}$ compare the relative importance of \mathbf{x} versus p , they can be directly compared across models run on different data sets. In contrast, in the preference space the coefficients in $\boldsymbol{\beta}$ compare the relative importance of \mathbf{x} versus standardized noise, which can vary across data sets and therefore cannot be compared without accounting for potential differences in scale. Because of these advantages, we conduct our analysis in the WTP space. Since our analysis relies on simulation with models estimated on multiple data sets, the WTP space facilitates the comparability of model coefficients and also provides directly interpretable results that have meaningful value without the need for post-hoc computations.

³WTP is somewhat of a misnomer as it suggests a threshold above which customers won't buy, whereas in the MNL model purchase probability varies continuously with price. A better name would be "equivalence price," i.e. the prices at which an alternative with a particular feature has equal utility as one without the feature.

⁴While true for MNL models, research has shown that placing convenient distributions, such as normal or log-normal, on parameters in hierarchical models results in different implications for the distributions of WTP when placed on parameters in the WTP space versus preference space [55, 99].

4.4.2 The Pooled RP-SP Model

Our description of the pooled utility model builds on the description in Chapter 8 of Louviere et al. (2000) by transforming it into the WTP space and including a broader range of attributes [32].

We focus on a general setting where the utility for each respective data source is given by

$$u_{jt}^R = \lambda^R \left[p_{jt} + \boldsymbol{\beta}^{R'} \mathbf{x}_{jt} + \boldsymbol{\gamma}^{R'} \mathbf{y}_{jt}^R + \left(\boldsymbol{\gamma}^{S'} \mathbf{y}_{jt}^S + \boldsymbol{\zeta}' \mathbf{z}_{jt} \right) \right] + \varepsilon_{jt}^R \quad (4.4)$$

$$u_{jt}^S = \lambda^S \left(p_{jt} + \boldsymbol{\beta}^{S'} \mathbf{x}_{jt} + \boldsymbol{\gamma}^{S'} \mathbf{y}_{jt}^S \right) + \varepsilon_{jt}^S \quad (4.5)$$

where the superscripts “R” and “S” refer to the data source (RP and SP, respectively). In these models, λ scales the coefficients relative to the standardized error and can be thought of equivalently as the reciprocal of scale of the error term, p is price, $\boldsymbol{\beta}$ is a vector of WTP parameters for non-price attributes \mathbf{x} that exist in both data sources, $\boldsymbol{\gamma}^R$ and $\boldsymbol{\gamma}^S$ are vectors of WTP parameters for non-price attributes \mathbf{y}^R and \mathbf{y}^S that are specific to each respective data source, and $\boldsymbol{\zeta}$ is a vector of WTP parameters for attributes \mathbf{z} that affect consumer choice in the RP context but are unobserved to the modeler. Note that λ^R and λ^S are not necessarily equal because the scale of the error relative to the attributes may be different in the two data sets.

The terms in parentheses in equation 4.4 ($\boldsymbol{\gamma}_n^{S'} \mathbf{y}_{jt}^S + \boldsymbol{\zeta}' \mathbf{z}_{jt}$) affect choices made in the market but are unobserved by the modeler; as a result, these terms are often left out of the specification of estimated models and absorbed in the error term. As an example, consider a researcher modeling preferences for car attributes. Let’s say the modeler knows that both *color* and *style* influenced consumer choices in an RP data set but neither were observed; however, *color* was a manipulated attribute in a SP data set. Under the true data generating mechanism *color* would exist in \mathbf{y}^S and *style* would exist in \mathbf{z} , and both would contribute to the underlying RP utility function despite being unobserved in the RP data set. Also note that \mathbf{y}^R and \mathbf{z} are omitted from the SP utility specification in equation 4.5 because those attributes are not presented to the survey respondent and therefore cannot affect choice. We assume that equations 4.4 and 4.5 represent the true data generating process and that we have access to data generated from each equation.

Our estimation goal is to recover the parameters $\boldsymbol{\beta}^R$ so that we can understand how changes

in the attributes will affect market choices. Given this goal, we might estimate a model exclusively from RP data, but this has several major disadvantages that have motivated much of the prior work on pooled models. If we only use the RP data, coefficients may be endogenous and/or inefficient in cases with high multicollinearity, and we would be unable to make any inference about $\boldsymbol{\gamma}^S$ since those attributes are not observed in the RP data.

The pooled model restricts equations 4.4 and 4.5 to have the same parameters for common attributes (α for *price* and $\boldsymbol{\beta}$ for \mathbf{x}) except for differences in scale: $\lambda^R \alpha^R = \lambda^S \alpha^S$ and $\lambda^R \boldsymbol{\beta}^R = \lambda^S \boldsymbol{\beta}^S$ [32]. For identification purposes, one of the scale parameters must be set to a fixed value (typically $\lambda^R = 1$), and a single scale parameter, λ , is estimated that represents the *ratio* between the two scale parameters λ^S and λ^R . In the WTP space, the equivalent assumption is that the WTP parameters are equal for common parameters ($\boldsymbol{\beta}^R = \boldsymbol{\beta}^S = \boldsymbol{\beta}$) and the two scale terms are directly estimated. Under these assumptions, the estimated utility specification for each respective data source is given by

$$u_{jt}^R = \hat{\lambda}^R \left(p_{jt} + \hat{\boldsymbol{\beta}}' \mathbf{x}_{jt} + \hat{\boldsymbol{\gamma}}^{R'} \mathbf{y}_{jt}^R \right) + \varepsilon_{jt}^{R*} \quad (4.6)$$

$$u_{jt}^S = \hat{\lambda}^S \left(p_{jt} + \hat{\boldsymbol{\beta}}' \mathbf{x}_{jt} + \hat{\boldsymbol{\gamma}}^{S'} \mathbf{y}_{jt}^S \right) + \varepsilon_{jt}^{S*} \quad (4.7)$$

where $\hat{\boldsymbol{\beta}}$ is modeled as a vector of common parameters between the two utility models and the unobserved terms in the RP context are now part of the error term ε_{jt}^{R*} . The hats on the parameters indicate that they are estimated. The key assumption of the pooled model is that $\hat{\boldsymbol{\beta}}$ is common across equations 4.6 and 4.7; that is, the pooled model assumes the effect of the of the common attributes on consumer choices is the same across contexts. As we will show, if this assumption is false for any of the attributes, then $\hat{\boldsymbol{\beta}}$ will not be an unbiased estimate of the true $\boldsymbol{\beta}^R$, which could lead to erroneous conclusions about how consumers will react to changes in attributes. In the next sections, we discuss how endogeneity in the RP data and differences between the RP and SP contexts can violate this assumption.

4.4.3 Endogeneity

In RP data, when the number and nature of attributes in a choice situation is sufficiently large and complex, it is reasonable to assume that any discrete choice model will omit some unobserved information about attributes that influence choice; that is, there are important variables that affect choice in \mathbf{z} and these variables are omitted from estimated models. This misspecification will lead to biased parameter estimates if any of the observed attributes are correlated with the unobserved attributes and proper measures are not taken to account for the endogeneity [30, 66, 100]. In particular, it is very plausible that companies are setting prices to reflect the unobserved attributes and so when \mathbf{z} is left out of the estimated model, the resulting endogeneity between price and the error term may bias the estimates of price response downward.⁵

In the pooled model, if a term in the omitted \mathbf{z} , was positively correlated with price, then the estimated WTP parameters $\hat{\boldsymbol{\beta}}$ and $\hat{\boldsymbol{\gamma}}^R$ will be biased upward (assuming a negative relationship between price and utility and a positive coefficient on the term in \mathbf{z}), which can be interpreted as overestimating the size of consumer WTP for changes in attributes \mathbf{x} and \mathbf{y}^R . Importantly, if the underlying true preference parameters were the same between RP and SP contexts, the endogeneity in the RP data would violate the pooling assumption of $\hat{\boldsymbol{\beta}}^R = \hat{\boldsymbol{\beta}}^S = \hat{\boldsymbol{\beta}}$.

4.4.4 Differences in Contexts

It is well-known that context alters choice behavior [73, 74, 101], so, although the RP and SP models share common product attributes, the true utility model parameters for those attributes may not be equal for multiple reasons. If the samples include different individuals, then those individuals may simply have different preferences, and even if the individuals are the same, their choice behavior may differ between survey and market contexts.

To represent differences between RP and SP contexts, we allow the true SP WTP parameters to be multiples of the true RP WTP parameters. The vector of WTP parameters $\boldsymbol{\beta}^S$ in equation 4.5 is assumed to be related to the corresponding $\boldsymbol{\beta}^R$ in equation 4.4 by $\boldsymbol{\beta}^S = \boldsymbol{\delta} \circ \boldsymbol{\beta}^R$ where $\boldsymbol{\delta}$ represents a vector of context effects for attributes \mathbf{x} . In the preference space, the equivalent context effect would be specified as $(\boldsymbol{\beta}^S/\alpha^S) = \boldsymbol{\delta} \circ (\boldsymbol{\beta}^R/\alpha^R)$. It is important to note that here $\boldsymbol{\delta}$ is

⁵While endogeneity is not unique to RP data, it is often assumed irrelevant in SP data since SP surveys are controlled experiments and the researcher observes all attributes influencing choice.

not a vector of estimated parameters but rather a vector of constants in the data-generating process that allows parameters for the same attributes in two data sets to differ. Our goal is to determine the performance of the (misspecified) pooled model under these circumstances. We specifically investigate the case where the coefficient for a non-price attribute is different between the RP and SP data sets.

4.5 Synthetic Data Study

In this section, we lay out a synthetic data study which aims to illustrate how endogeneity in the RP data can affect the ability of pooled models to recover the true data-generating parameters. We first generate multiple sets of RP and SP data under different conditions of endogeneity in the RP data and context differences in the SP data using known parameters and then estimate a series of pooled RP-SP models on those data. We then compare the resulting parameter estimates to the true RP market parameters.

We generate data based on the “true” utility models in equations 4.4 and 4.5. To illustrate the key points, we assume utility depends on price, p , a single non-price attribute, x , that is common to each data source, and a single unobserved RP attribute, z , that is used to control the level of price endogeneity in the RP data, depending on its correlation with price.⁶ The true models are given by

$$u_{jt}^R = \lambda^R (p_{jt} + \beta^R x_{jt} + \zeta z_{jt}) + \varepsilon_{jt}^R \quad (4.8)$$

$$u_{jt}^S = \lambda^S (p_{jt} + \beta^S x_{jt}) + \varepsilon_{jt}^S \quad (4.9)$$

where all parameters are scalar. Table 4.5 shows the true parameters used to generate the data for our base case and sensitivity analyses. Note that the model we estimate will not include z_{jt} as a predictor as it represents an attribute that affects consumer choice but is unobserved to the modeler.

⁶We also investigated cases where there are more than one non-price attribute and found the results to be similar.

4.5.1 Simulating the RP Data

We simulate the RP data to reflect the structure of typical RP data sets where a set of products is offered to a “market” and then many choices are observed for that set of products. For each RP data set, we generate T^R markets with N^R/T^R choices in each market where N^R is the total number of RP choice observations. Each market contains A^R alternatives that make up the choice set denoted by J_t^R . We generate the alternatives in each choice set J_t^R by randomly drawing p , x , and z from a multivariate normal distribution with mean $\boldsymbol{\mu} = [0, 0, 0]$ and variance-covariance matrix given by

$$\boldsymbol{\Sigma}^R = \begin{bmatrix} 1 & \rho_{px} & \rho_{pz} \\ \rho_{px} & 1 & \rho_{xz} \\ \rho_{pz} & \rho_{xz} & 1 \end{bmatrix} \quad (4.10)$$

where the relative correlations between attributes are given by the ρ terms. As a baseline, we set $\rho_{px} = \rho_{pz} = \rho_{xz} = 0$. To generate RP data with endogeneity, we set $\rho_{pz} > 0$ which induces price endogeneity when z is omitted from the estimated model (because it’s unobserved by the modeler). We also run sensitivity cases of different collinearity levels where $\rho_{px} \neq 0$ (see Table 4.5).

Shares for each alternative in each choice set J_t^R are computed using the familiar logit probability fraction that results from assuming the error term in the utility function is distributed by an IID Gumbel distribution:

$$P_{jt}^R = \frac{\exp[\lambda^R (p_{jt} + \beta^R x_{jt} + \zeta z_{jt})]}{\sum_{k \in J_t^R} \exp[\lambda^R (p_{kt} + \beta^R x_{kt} + \zeta z_{kt})]}, \quad \forall j \in J_t^R \quad (4.11)$$

To simulate individual choices in each market, we take N^R/T^R multinomial draws according to the choice probabilities.

4.5.2 Simulating the SP Data

To introduce a difference in consumer response between market and survey contexts, we compute β^S in the SP model by scaling β^R such that $\beta^S = \delta \beta^R$. Each set of SP data in each simulation is generated to approximate a typical conjoint survey. Each of N^S choice questions is generated

by randomly choosing A^S alternatives from the full factorial design using 5 levels (-2, -1, 0, 1, 2) for each attribute. As would be typical, the design prohibits any two identical alternatives from occurring within the same choice question. Choices are computed as the alternative in each choice question with the highest utility (equation 4.9), with the error term drawn from a standard IID Gumbel distribution for each alternative in each choice question.

4.5.3 Test Cases

Our experiment focuses on the ability to recover the true WTP parameter for x in the market context, β^R , under different conditions of ρ_{pz} and δ present when generating the data. We generate sets of RP and SP data using 6 different cases for ρ_{pz} and δ shown in Table 4.4 to cover the range of likely scenarios in real data sets. If $\rho_{pz} = 0$ and $\delta = 1$ (case 2), then the pooled model assumption that β^R and β^S are the same is valid and unbiased estimates of the true parameters are recovered by estimating a pooled model; however, any deviations from these conditions imply that the pooled model is misspecified and could result in estimates of $\hat{\beta}$ that differ from the true parameter β^R . By estimating a misspecified pooled model to the synthetic data, we can explore how well the pooled model recovers the true RP parameter.

Table 4.4: Test cases for generating synthetic RP and SP data

Case	ρ_{pz}	δ	Interpretation	
			RP Data	SP Data
1: "SP WTP Understated"	0	0.5	No price endogeneity	WTP for x understated
2: "Ideal"	0	1	No price endogeneity	No contextual differences
3: "SP WTP Overstated"	0	2	No price endogeneity	WTP for x overstated
4: "Two Wrongs Make a Right"	0.5	0.5	Price endogenous	WTP for x understated
5: "RP Price Endogenous"	0.5	1	Price endogenous	No contextual differences
6: "Wrong In The Same Way"	0.5	2	Price endogenous	WTP for x overstated

4.5.4 Simulation Parameters

The parameter values for the parameters other than ρ_{pz} and δ are described in Table 4.5. We use the Base Case to illustrate our main findings about how ρ_{pz} and δ affect pooled model estimates. We also conduct extensive sensitivity analyses using wide ranges of values for each parameter, as shown in Table 4.5 (see section 4.7 and the sensitivity figures in section B.2 of Appendix B).

In preparing data for a pooled model, it is important to consider how much information each data set contributes to the pooled parameter estimates [31]. As we will discuss in more detail below in our simulation, we chose to generate data sets that are balanced in terms of the information about the pooled parameters. This results in an approximately equal contribution to the parameter estimates from each data set (see Table 4.6, section 4.6.3 on information balance, and section B.1 in Appendix B on the relationship between data set characteristics and information). We achieve this balance by manipulating the number of attributes and alternatives in both data sets and the number of markets in the RP data. All of these factors contribute to the level of information in data sets and thus the precision of estimated parameters [102].

Table 4.5: Parameters used to generate synthetic RP and SP data

Parameter	Base Case	Sensitivity Range	Description
λ^R	1	[0.1, 5]	Scale of RP context error term
λ^S	1	[0.1, 5]	Scale of SP context error term
β^R	1	[-3, 3]	WTP coefficient for attribute x in RP context
β^S	$\delta\beta^R$	–	WTP coefficient for attribute x in SP context
ζ	1	[-1.5, 1.5]	WTP coefficient for unobserved attribute z in RP context
ρ_{px}	0	[0, 0.5]	Correlation between <i>price</i> and x
N^R	1,000	[500, 5,000]	Number of RP choice observations per simulation
N^S	2,000	[500, 5,000]	Number of SP choice observations per simulation
A^R	15	[3, 100]	Number of alternatives per RP market
A^S	3	[2, 10]	Number of alternatives per SP choice question
T^R	50	[1, 200]	Number of RP markets per simulation

For our base case, we chose the number of alternatives in the SP data to be $A^S = 3$ since conjoint surveys typically have low numbers of alternatives per choice question to reduce the cognitive burden on respondents. Likewise, we chose the number of alternatives in the RP data to be $A^R = 15$ since real markets often have many more alternatives than those in SP data. Since $A^R > A^S$ give the RP data more information, we chose $N^R < N^S$ to balance the information in each data set.⁷ Finally, we chose $T^R = 50$ to increase the variation in the design matrix for the RP data. While 50 independently simulated markets is highly atypical in real RP data sets, we use this as a conservative

⁷The Fisher information matrix was computed and compared for multiple data sets simulated using these baseline parameters to ensure balance.

case that provides an optimistically high level of information. Fewer, more correlated markets only reduces the level of attribute variation and thus increases the sampling variance in the parameter estimates across multiple simulations; more importantly, less informative RP data tilts the balance of information toward the SP data, resulting in parameters that are more heavily influenced by the SP data.

4.5.5 Model Estimation

For each pair of simulated RP and SP data sets, we estimate the following pooled RP-SP model:

$$u_{jt}^R = \hat{\lambda}^R (p_{jt} + \hat{\beta}x_{jt}) + \varepsilon_{jt}^{R*} \quad (4.12)$$

$$u_{jt}^S = \hat{\lambda}^S (p_{jt} + \hat{\beta}x_{jt}) + \varepsilon_{jt}^{S*} \quad (4.13)$$

where $\hat{\beta}$ is common between the two models. Note that z is omitted from the utility specification in equation 4.12; as a result, price will be endogenous when $\rho_{pz} \neq 0$. Assuming the error terms are distributed IID Gumbel, then the probabilities for each data source are given by the multinomial logit fraction such that

$$\hat{P}_{jt}^R = \frac{\exp \left[\hat{\lambda}^R (p_{jt} + \hat{\beta}x_{jt}) \right]}{\sum_{k \in J_t^R} \exp \left[\hat{\lambda}^R (p_{kt} + \hat{\beta}x_{kt}) \right]}, \quad \forall j \in J_t^R \quad (4.14)$$

$$\hat{P}_{jt}^S = \frac{\exp \left[\hat{\lambda}^S (p_{jt} + \hat{\beta}x_{jt}) \right]}{\sum_{k \in J_t^S} \exp \left[\hat{\lambda}^S (p_{kt} + \hat{\beta}x_{kt}) \right]}, \quad \forall j \in J_t^S \quad (4.15)$$

The parameters in equations 4.12 and 4.13 are estimated by maximizing the pooled log-likelihood which is equal to the sum of the multinomial log-likelihoods of the RP and SP data:

$$L = \sum_n \sum_t \sum_j y_{njt} \ln \hat{P}_{jt}^R + \sum_n \sum_t \sum_j y_{njt} \ln \hat{P}_{jt}^S \quad (4.16)$$

where $y_{nit} = 1$ if person n chooses alternative j in market t , and 0 otherwise, and \hat{P}_{jt}^R and \hat{P}_{jt}^S are the logit fractions given by equations 4.14 and 4.15. Since the log-likelihood is nonlinear in

parameters, we use a multi-start algorithm to search for a global solution. In each of 10 iterations, we maximize the log-likelihood using a different set of random starting points between -1 and 1 and store the result, and then we select the solution with the greatest log-likelihood. For our base case simulation experiment, the algorithm converged to the same solution in all 10 multi-start iterations for 91% of the simulations, and the maximum difference in the log-likelihood across all 10 multi-start iterations was less than 0.001 for 99% of the simulations.

4.6 Results

4.6.1 Parameter Estimates

We simulate 100 sets of RP and SP data for each test case in Table 4.4 and then used them to estimate RP, SP, and pooled models. Figure 4.2 shows the ratio between the estimated and true model WTP coefficients for each test case. Results are presented as box plots of all 100 simulations on a logarithmic scale for comparing ratios.

In Figure 4.2a, price is not endogenous in the RP data, and the difference in the SP context varies from underestimating β^R in case 1 when $\delta = 0.5$ to overestimating β^R in case 3 when $\delta = 2$. As would be expected, the LR test rejects pooling in cases 1 and 3 and largely accepts pooling in case 2 when $\delta = 1$. Note that even though the true parameters are the same in case 2, the LR test still rejects pooling in 26% of the simulations; we discuss this result further in section 4.6.2.

In Figure 4.2b, price is endogenous in the RP data which has several important effects depending on the value of δ . In case 4, the upward bias on $\hat{\beta}$ created by the price endogeneity in the RP data is partially balanced by the context difference in the SP data where $\delta = 0.5$ (hence the name “Two wrongs make a right”). In case 6, the opposite situation occurs as the price endogeneity in the RP data and context difference in the SP data where $\delta = 2$ both have similar affects on $\hat{\beta}$; as a result, the estimated $\hat{\beta}$ in the pooled model is nearly the same as those in the RP and SP models (hence the name “Wrong in the same way”).

Unfortunately, the LR test is no longer informative in determining whether SP and RP data should be pooled in the presence of endogeneity in the RP data. The LR test rejects pooling in case 4 when pooling actually helps mitigate the RP and SP biases and largely accepts pooling in case 6 when pooling does not improve the biases. However, in case 6 the RP and SP data produce

biases in the same *direction* and *magnitude*, which may not always be the case in real data sets; if the bias magnitudes were different, the LR test may still reject pooling even if the biases were in the same direction.

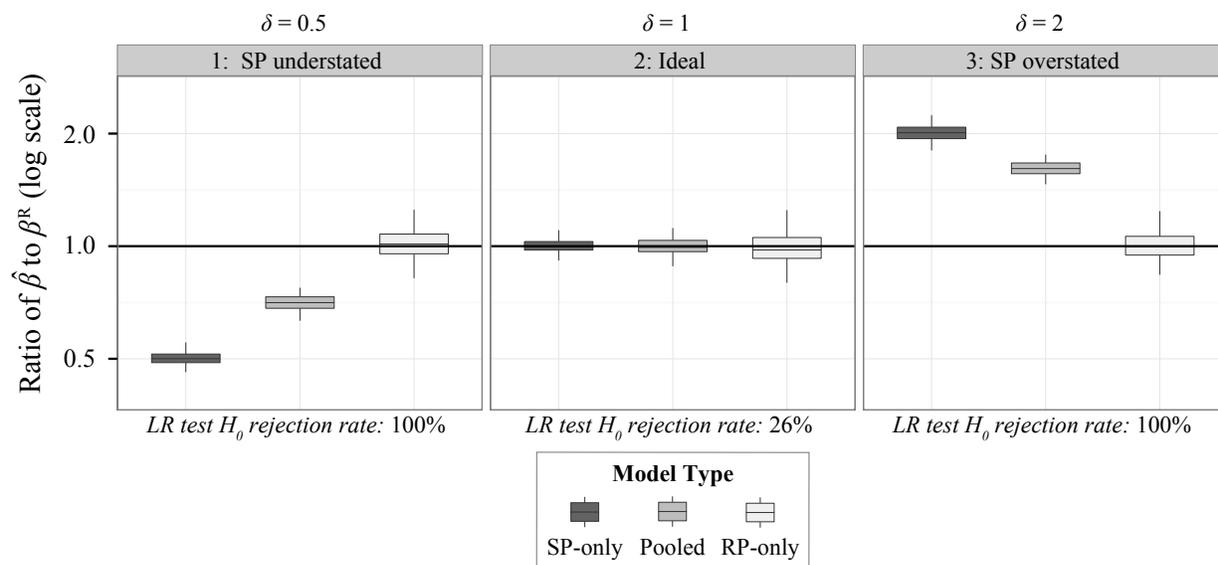
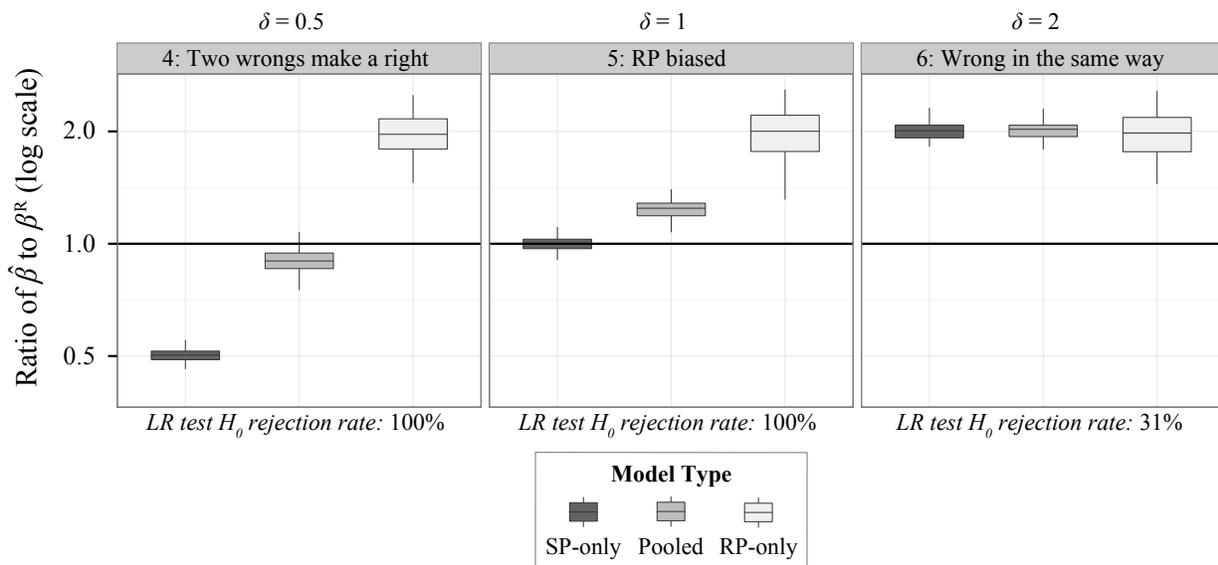
(a) No RP Price Endogeneity ($\rho_{pz} = 0$)(b) RP Price Endogenous ($\rho_{pz} = 0.5$)

Figure 4.2: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β^R for each test case. Each box plot represents results from 100 simulated data sets using the base case parameters in Table 4.5.

Another important observation is that the values of ρ_{pz} and δ affect the results for all parameters, not just the the WTP parameters. Figure 4.3 shows the ratio of estimated to true parameters for all of the pooled model parameters. Depending on the case, the modeler could make false conclusions about both consumer WTP for attributes as well as how consistently consumers make choices in the RP versus SP contexts. For example, in case 2 the RP scale parameter is less than one because the omitted unobserved variable increases the variance of the error term (thus decreasing scale). The presence of endogeneity exacerbates the effect; in particular, in case 6 when the LR test would largely accept pooling, the modeler may falsely conclude that respondents make much more consistent choices in the RP context than SP context.

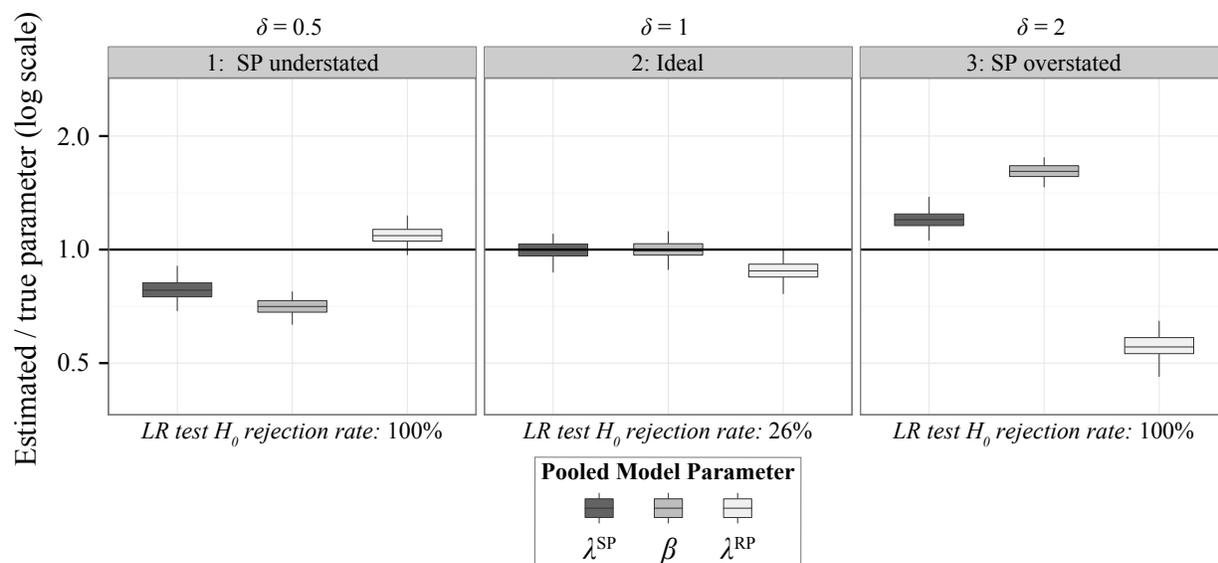
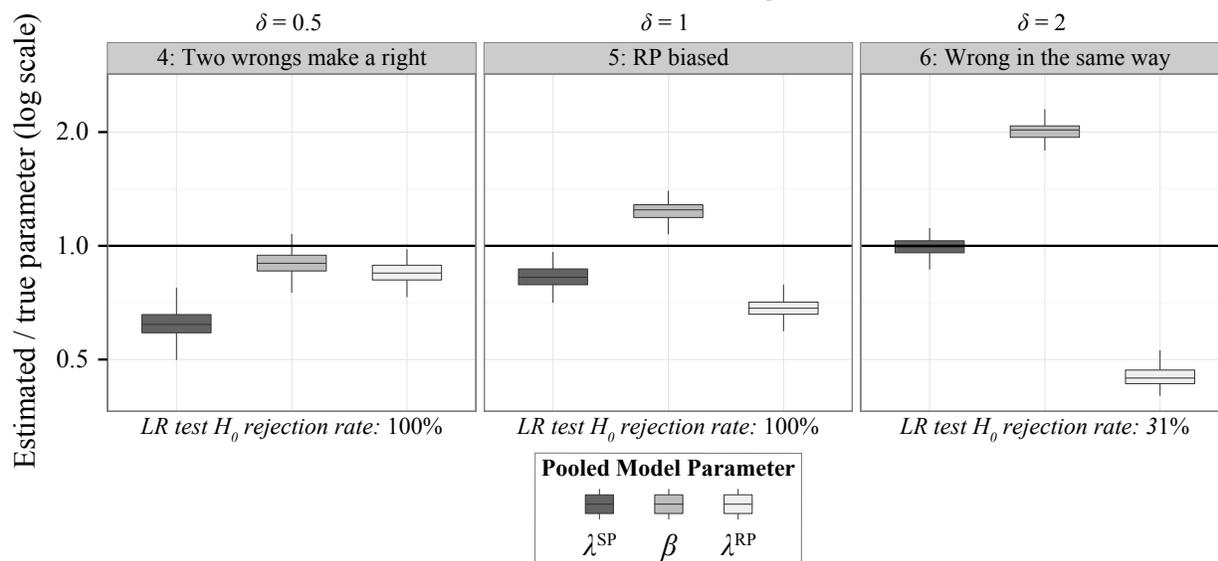
(a) No RP Price Endogeneity ($\rho_{pz} = 0$)(b) RP Price Endogenous ($\rho_{pz} = 0.5$)

Figure 4.3: Ratio of estimated to true RP parameters for all pooled model parameters for each test case. Each box plot represents results from 100 simulated data sets using the base case parameters in Table 4.5.

4.6.2 Sensitivity of the Likelihood Ratio Test

The standard LR test statistic is computed as $-2[(L^R + L^S) - L^P]$, where L^R and L^S are the log-likelihood values from the separately estimated RP and SP models, respectively, and L^P is the log-likelihood of the pooled model. The test statistic is asymptotically chi-squared distributed with the degrees of freedom equal to the extra number of parameters estimated for the separate

RP and SP models relative to that of the pooled model. If the test statistic is less than a critical value at a chosen significance level (e.g. $\alpha = 0.05$), then the test fails to reject the null in favor of pooling; likewise, rejecting the null implies that attributes common to each data set have different parameters and should not be pooled.

We apply the standard LR test for the test cases in our simulation experiment. Figure 4.4 shows the LR test rejection rates for 100 simulated data sets in each test case. We examine the test’s sensitivity to sample size by varying N^R and N^S and sensitivity to attribute variation in the data by varying T^R .

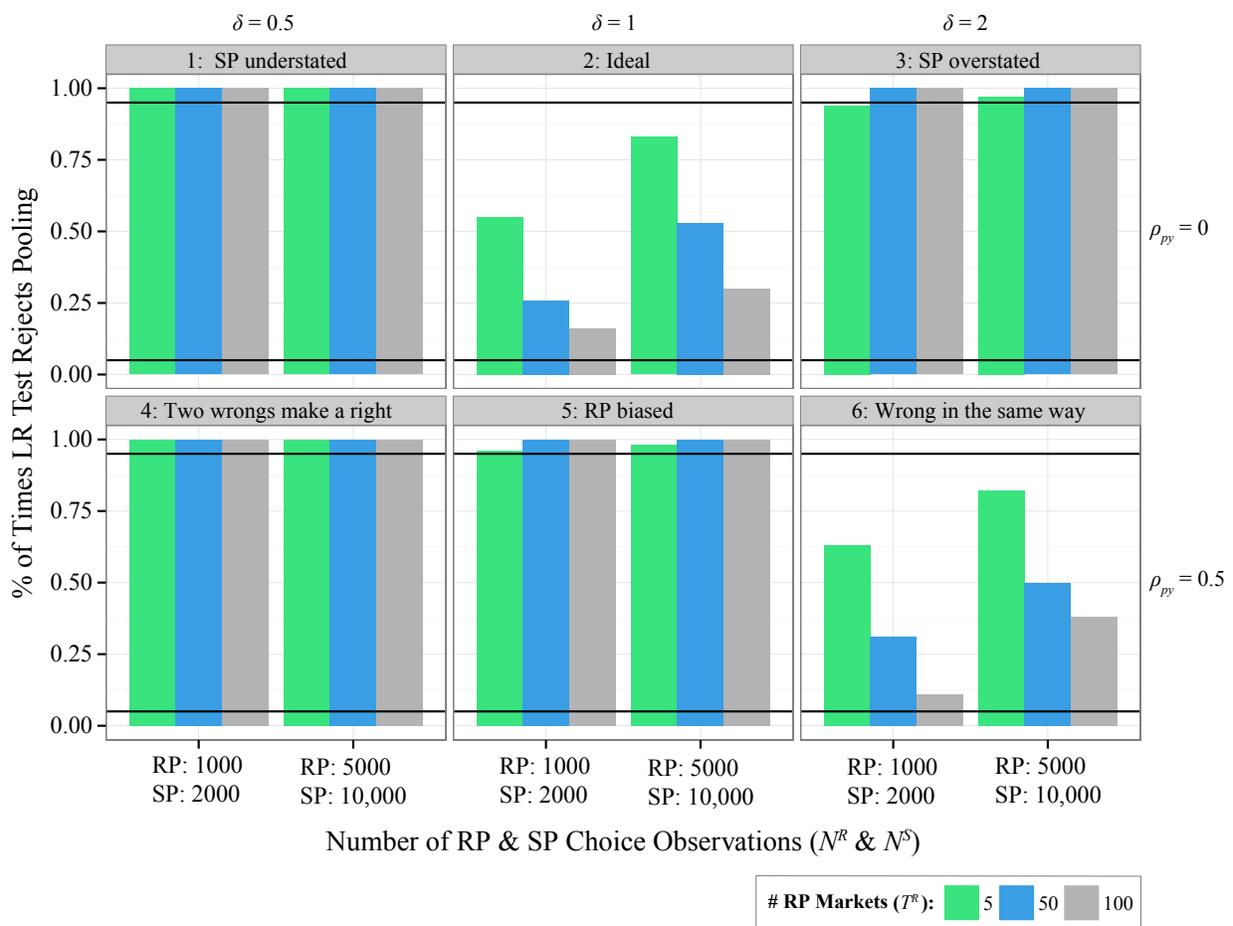


Figure 4.4: Percent of times the likelihood ratio test rejects the null hypothesis ($\beta^R = \beta^S$) as a function of ρ_{pz} , δ , T^R , N^R , and N^S . Each bar is computed from 100 simulations using the parameters in Table 4.5. Horizontal black lines indicate a 0.05 significance level.

In general, we find the LR test is sensitive to both sample size and attribute variation. The test performs as would be expected (reject the null) in cases 1, 3, 4, and 5 because one or both of the data sources has a characteristic (price endogeneity or context difference) that makes the WTP parameter in the RP and SP models unequal. However, in case 2 where the true parameters are actually the same and pooling should be accepted, the LR test still rejects pooling large portions of the time when the number of RP markets is low (i.e. when RP attribute variation is low). A similar result occurs in case 6 when the parameter biases are in the same direction and have similar magnitudes. In these cases, increasing the number of observations while holding the number of markets fixed increases the likelihood that the LR test will reject the null due to randomness in the (non-orthogonal) set of products available in each market becoming more statistically significant as more data are collected. In addition, increasing the number of markets while holding the number of observations fixed reduces the likelihood that the LR test will reject the null because the increased variation of the product attributes improves average estimates of the parameters.

4.6.3 Information Balance

Different data sources have different levels of information about the parameters that we intend to estimate. Data sets with small samples or multicollinearity will result in imprecise parameter estimates, while large data sets with ample variation in the attributes will result in more precise parameter estimates. The amount of information in a choice data set can be influenced by a number of factors, including the number of observations, the levels of correlation and variation among observed attributes, the number of different choice sets, and the number of alternatives in the choice sets. Importantly, having a large sample size does not always guarantee large amounts of information [102]. For example, even with fewer observed choices, SP data are often highly informative because the choice observations come from many different choice sets with alternatives and attributes that are chosen specifically to create variation in the attributes and precise parameter estimates. RP data often have large sample sizes but can remain relatively uninformative if (in the worst of cases) they have only one choice set and/or highly correlated attributes.

The pooled log-likelihood in equation 4.16 implicitly weights parameter estimates by the respective amounts of information available in the RP and SP data. In cases where the RP and SP parameters are actually the same, this weighting should not impact the pooled model estimates

(see case 2 in Figure 4.2a). However, in case 4 in Figure 4.2b, the relative weighting could shift the pooled estimate more towards either the SP model or RP model estimate. One way to characterize this implicit weighting is to compare the Fisher information matrix, \mathbf{I} , for each data set, which measures the amount of information a data set carries about the unknown model parameters. The information matrix for a data set can be computed as the negative of the second derivative of the log-likelihood function⁸, given by

$$\mathbf{I} = -\frac{\partial^2 L}{\partial \hat{\beta}_k \partial \hat{\beta}_l} = \sum_{n=1}^N \sum_{t=1}^T \sum_{i=1}^{J_t} \hat{P}_{it} \begin{bmatrix} x_{nitk} - \sum_{j \in J_t} x_{njtk} \hat{P}_{jt} \\ \vdots \\ x_{nitl} - \sum_{j \in J_t} x_{njtl} \hat{P}_{jt} \end{bmatrix} \begin{bmatrix} x_{nitk} - \sum_{j \in J_t} x_{njtk} \hat{P}_{jt} \\ \vdots \\ x_{nitl} - \sum_{j \in J_t} x_{njtl} \hat{P}_{jt} \end{bmatrix} \quad (4.17)$$

We use the determinants of the information matrices⁹ from each data source, $\det(\mathbf{I}^R)$ and $\det(\mathbf{I}^S)$, to define a metric ω that ranges from 0 to 1 which indicates the proportion of information coming from the SP data set:

$$\omega = \frac{\det(\mathbf{I}^S)}{\det(\mathbf{I}^R) + \det(\mathbf{I}^S)} \quad (4.18)$$

The value of ω can be computed before pooling two data sets to gain an understanding of the naturally occurring balance of information.¹⁰ For interpretation, $0 < \omega < 0.5$ implies that there is more information in the RP data, $0.5 < \omega < 1$ implies that there is more information in the SP data, and $\omega = 0.5$ implies that the information is equal between the two data sources.

As previously stated, we chose our base case simulation parameters to produce data sets with relatively balanced information. As a check, we simulated 100 RP and SP data sets for each test case using the base case parameters in Table 4.5 and then computed the mean ω and mean $\det(\mathbf{I})$ at the true parameters across all 100 simulations. Table 4.6 confirms that our base case parameters produce relatively balanced data sets on average.

⁸The information matrix presented in equation 4.17 is for a general model rather than for the specific simulation experiment in this study.

⁹The determinant is frequently used as a scalar measure of the overall information in the data. For example, the experimental design approach known as D-efficiency selects the values of the attributes to maximize the determinant of the Fisher Information.

¹⁰Note that \mathbf{I} is computed at a set of parameters. We suggest using the RP model and SP model maximum likelihood parameters to compute ω .

Table 4.6: Balance of information between simulated RP and SP data sets

Case	mean(ω)	mean(det(\mathbf{I}))	
		RP Data	SP Data
1: “SP WTP Understated”	0.48	150200	140400
2: “Ideal”	0.48	150200	140500
3: “SP WTP Overstated”	0.48	151600	141200
4: “Two Wrongs Make a Right”	0.49	149000	141000
5: “RP Price Endogenous”	0.48	153500	141000
6: “Wrong In The Same Way”	0.49	150800	141400

Because the baseline parameters used in the simulations result in a relatively even balance of information, the WTP coefficients in Figure 4.2 for the pooled models are approximately half way between those for the SP and RP models. However, by changing the simulation parameters, the information could be higher in one of the data sets and the pooled model WTP coefficient estimates would be closer to that of either the RP model or SP model. Figure 4.5 below shows how different balances of information between RP and SP data sets can change the outcome of pooled model estimates for case 4 ($\rho_{pz} = 0.5$, $\delta = 0.5$). The information balance is varied by modifying the SP sample size (N^S).

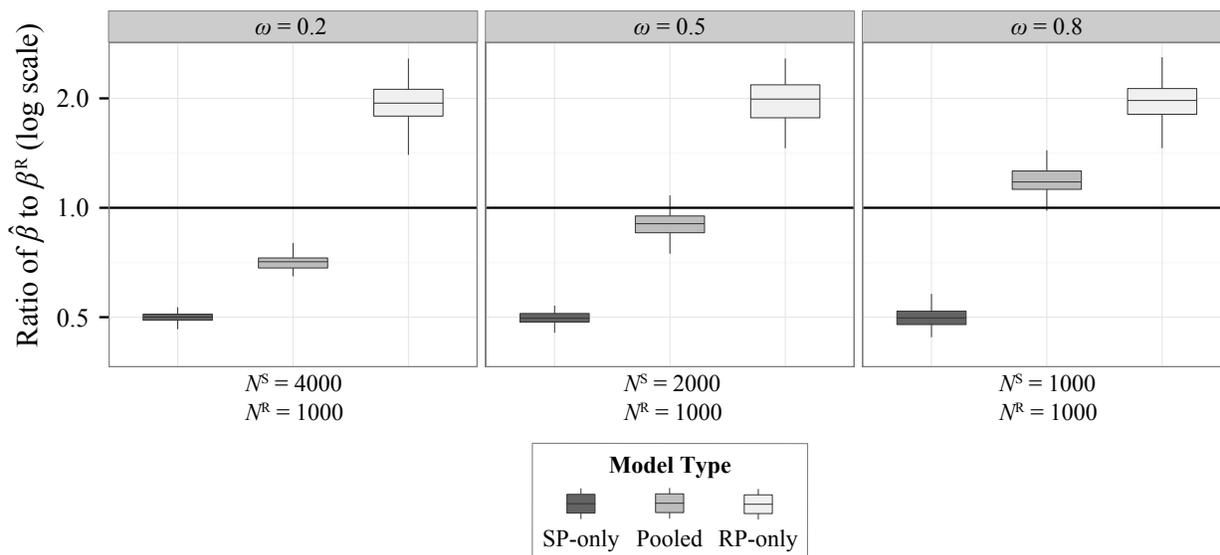


Figure 4.5: Sensitivity of information balance in SP, RP, and pooled model results of $\hat{\beta}/\beta^R$ for test case 4 ($\rho_{pz} = 0.5$, $\delta = 0.5$). Each box plot represents results from 100 simulated data sets using the base case parameters in Table 4.5 but with different values of N^S and thus different information balances.

4.7 Sensitivity Analysis

The parameters chosen for our base case in Table 4.5 had particularly ideal characteristics that are atypical in real data sets (e.g. 50 independent RP markets with exactly the same market size). Nonetheless, while these parameters were chosen to make clear illustrations of the range of possible outcomes across our test cases, we conduct an extensive sensitivity analysis by running simulations across the full sensitivity range of each parameter in Table 4.5. For each parameter, we compare the WTP results as in Figure 4.2 as well as the LR test rejection rates. Figures for each sensitivity case are shown in section B.2 of Appendix B.

Table 4.7 summarizes the qualitative effect of each sensitivity case. Every case except for changes in β^R results in either increasing or decreasing the amount of information in one of the data sets, impacting the relative balance of information in the pooled model. In addition, the parameters λ^R , λ^S , N^R , N^S , A^R , A^S , and T^R all affect the sampling variance across multiple simulations. Both the information balance and sampling variance impact the performance of the LR test. In general, increased sampling variance decreases the rejection rates in cases 2 and 6 (where the RP and SP parameters are nearly the same).

In addition to these general observations, we also observe that the sign and magnitude of the ζ coefficient (the WTP coefficient for the unobserved attribute z) greatly impact our conclusions about the LR test in the presence of endogeneity in the RP data. As we noted in section 4.6.1, our base case for test case 6 results in biased estimates of $\hat{\beta}$ that share the same direction and magnitude from the RP and SP data; as a result, the LR test largely fails to reject pooling. However, when we increase the size of ζ , the bias from the endogeneity in the RP data becomes larger in magnitude than that from the SP data, and the LR test largely rejects pooling. Thus the direction and *magnitude* of a bias from either data source both impact the performance of the LR test. Likewise, when ζ is negative, cases 4 and 6 swap in their interpretation, with case 4 having biases in the same direction from each data source and case 6 having biases in opposite directions.

Table 4.7: Summary of sensitivity cases

Parameter	Base Case	Sensitivity Case	Variance in WTP Estimates	Information in RP Data	Information in SP Data	Pooled Model Information Balance	LR Test Results
λ^R	1	0.1	Increases	Decreases	–	SP greater	Decreases rejection rates across all test cases
		5	Decreases	Increases	–	RP greater	Increases rejection rates across all test cases
λ^S	1	0.1	Increases	–	Decreases	RP greater	Decreases rejection rates across all test cases
		5	Decreases	–	Increases	SP greater	Increases rejection rates across all test cases
β^R	1	-3 3	– –	– –	– –	– –	– –
ζ	1	-1.5	–	Decreases	–	SP greater	–
		1.5	–	Decreases	–	SP greater	Increases rejection rate for case 6
ρ_{px}	0	0.5	–	Decreases	–	SP greater	Decreases rejection rates in cases 2 and 6
N^R	1000	500	Increases	Decreases	–	SP greater	Decreases rejection rates in cases 2 and 6
		5000	Decreases	Increases	–	RP greater	Increases rejection rates in cases 2 and 6
N^S	2000	500	Increases	–	Decreases	RP greater	Decreases rejection rates in cases 2 and 6
		5000	Decreases	–	Increases	SP greater	Increases rejection rates in cases 2 and 6
A^R	15	3	Increases	Decreases	–	SP greater	Increases rejection rates in cases 2 and 6
		100	Decreases	Increases	–	RP greater	Decreases rejection rates in cases 2 and 6
A^S	3	2	Increases	–	Decreases	RP greater	Decreases rejection rates in cases 2 and 6
		10	Decreases	–	Increases	SP greater	Decreases rejection rates in cases 2 and 6
T^R	50	1	Increases	Decreases	–	SP greater	Largely rejects pooling in all test cases
		200	Decreases	Increases	–	RP greater	Decreases rejection rates in cases 2 and 6

In addition to assessing the sensitivity of changing each simulation parameter, we also run a case with five common attributes in \mathbf{x} since the base case simulation only includes one pooled attribute, x . In this case, we model x_1 as the only attribute that has a difference between RP and SP contexts (controlled by δ). Figure 4.6 below shows the WTP coefficients from 100 simulations of this model. Results are nearly identical with those in Figure 4.3 except that the additional WTP coefficients for x_2 through x_5 in cases 4 through 6 are also biased upward due to the fact that price endogeneity affects all WTP coefficients. We also ran a case with five common attributes, three RP-specific attributes, and three SP-specific attributes, and results were again similar to those in Figure 4.6.

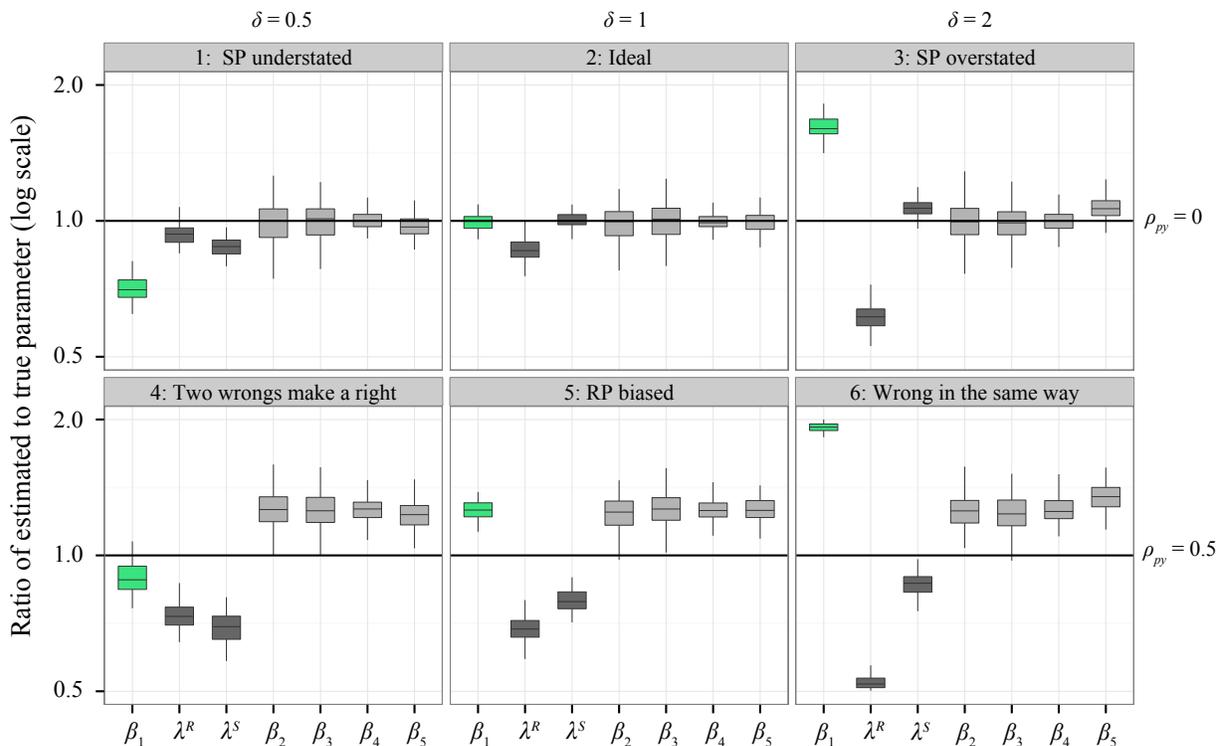


Figure 4.6: Ratio of estimated to true parameters for pooled model with 5 attributes. The context effect controlled by δ only affects β_1 . Each box plot represents 100 simulations using the parameters in Table 4.5.

4.8 Pooling Guidelines

Our simulation results have shown that pooled model parameter estimates are sensitive to the data generating conditions (i.e. endogeneity and contextual differences) as well as the balance of information between RP and SP data sets. The broad claim that pooling mitigates the weaknesses

of RP and SP data may only be true in some contexts in terms of parameter recovery. Given this understanding, we propose a new set of guidelines for pooling RP and SP data when the purpose of the model is to accurately estimate parameter values.¹¹ Notably, these guidelines include considerations for the possibility of endogeneity or other potential causes of bias in the RP data. Figure 4.7 below illustrates these proposed pooling guidelines.

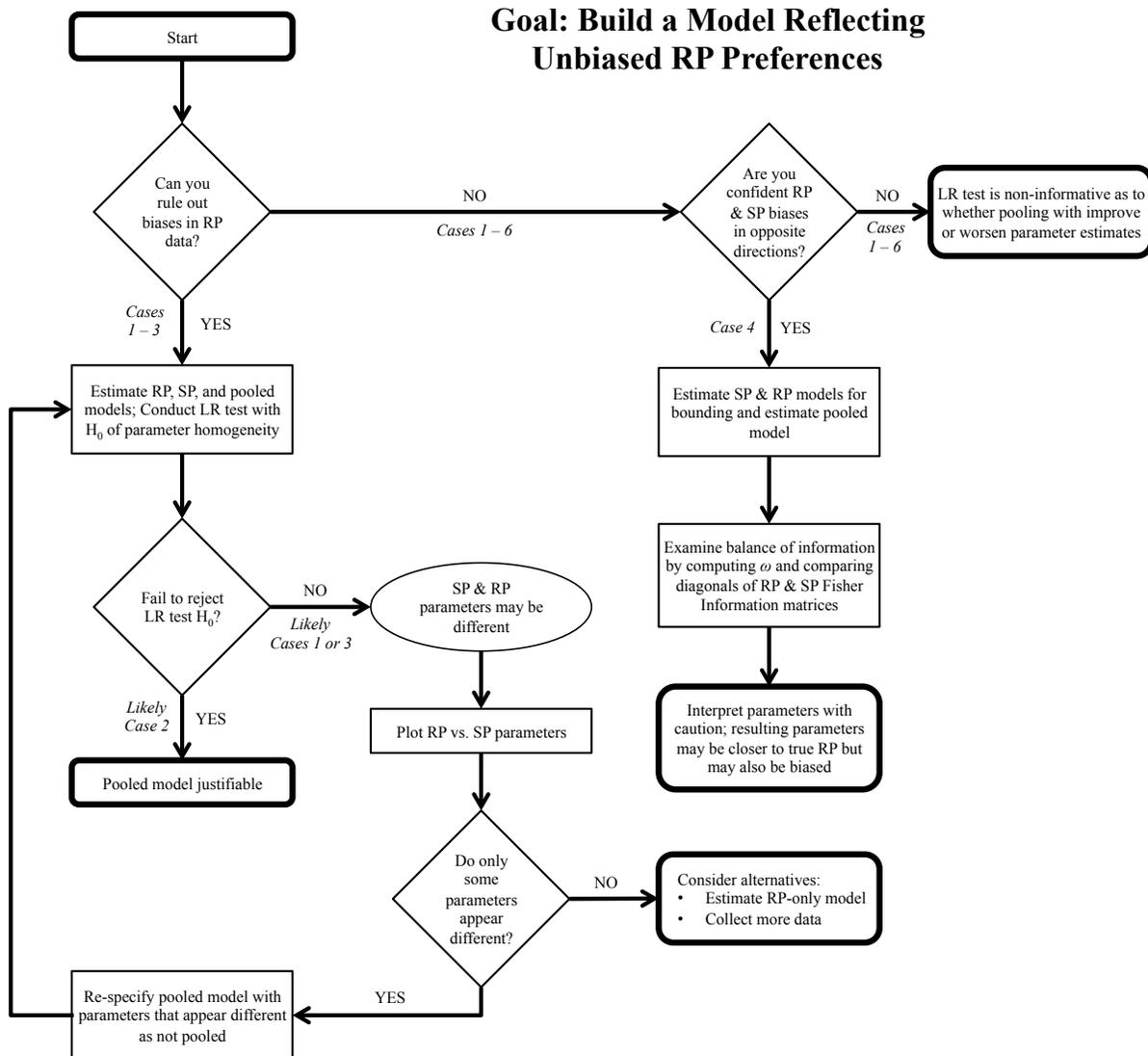


Figure 4.7: Proposed pooling guidelines incorporating dealing with biases in the RP data.

¹¹We make a distinction here with studies interested in building predictive models that predict well; it is not guaranteed that models with unbiased coefficient estimates will necessarily improve predictive performance.

4.9 Limitations

One limitation of this study is that our primary results are based on a simulation experiment rather than actual data. While our sensitivity analyses shows that our key findings are robust to different utility functions and data generation assumptions, our experiment makes several simplifying assumptions. For example, the homogeneous multinomial logit model used in this experiment has the Independence of Irrelevant Alternatives (IIA) property [30]. While it is unclear how pooled models will be affected by more flexible substitution patterns such as mixed logit models [36, 46] or hierarchical models [31], we expect our results will still hold since misspecified models with endogenous parameters will bias parameter estimates regardless of the model structure.

We also do not address concerns with state-dependence effects (e.g. when RP choices an individual makes influences his or her SP choices) or serial correlations across multiple responses in cases where the RP and SP respondents are the same [88, 96]. In addition, while we focus on price endogeneity from omitted variables and context effects as two specific modeling issues that could affect parameter estimates, there are a number of other modeling concerns that we have not addressed that could also affect parameter estimates, such as other forms of model misspecification and measurement error. In choosing endogeneity as a specific issue, our goal was to demonstrate how pooled model estimates are affected when using RP data with a feature that produces biased parameter estimates.

4.10 Conclusions

Endogeneity is a known concern in RP data. Using a synthetic data experiment, we test the performance of pooled RP-SP models in recovering true preference parameters under conditions of endogeneity in RP data and differences in consumer choice behavior between the RP and SP contexts. We find that the presence of endogeneity in the RP data can greatly affect the pooled model parameter estimates. In addition, in the presence of endogeneity, the likelihood ratio test is neither necessary nor sufficient to determine whether pooling will improve or worsen parameter estimates.

If the goal is to build a model that reflects unbiased marketplace preferences, the modeler should

consider the context and conditions under which the data were generated and attempt to rule out whether RP data sources could produce biased parameter estimates before making pooling choices. We provide new guidelines to help inform this decision. Finally, in cases where pooling may be able to mitigate RP and SP biases that are likely in opposite directions, examining the relative balance of information between two data sets can help provide an understanding of the relative weight each data set may contribute to parameter estimates. We provide a method for computing and comparing this balance to help guide interpretation of model results.

Chapter 5

Up, Down, and Sideways: Innovation in China and the Case of Plug-in Vehicles

5.1 Study Overview

In this Chapter, we use sales data, archival data, and 37 qualitative interviews with automotive managers and engineers, government officials, researchers, journalists, and industry consultants to study the variety of innovation directions independent Chinese firms are taking in China’s plug-in vehicle sector. We identify three distinct directions of innovation (“up,” “down,” and “sideways”) with respect to vehicle technology and organizational and business strategies. Our findings suggest that the interaction between national and regional regulatory regimes, a large heterogeneous market, and historical path dependencies of firms may be supporting a rich and diverse innovation environment in China’s plug-in vehicle sector. We find that while national institutions such as the joint venture system may be inadvertently discouraging innovation and diffusion of electric vehicle technologies in both the foreign and domestic arms of joint ventures, regional institutions such as local protectionism may be serving as incubators for a variety of innovations within independent domestic firms in their early development stages. In addition, the size and heterogeneity of China’s

The study presented in this chapter is based on a working paper. The use of first person plural includes coauthors Erica Fuchs, Yanmin Wang, Valerie Karplus, and Jeremy Michalek.

domestic market may be large enough to enable demand for the large variety of innovations. As these domestic firms begin to grow beyond their protected regional markets, China's institutions may need to evolve to support national standardization of policies and plug-in infrastructure.

5.2 Introduction

In recent years, the Chinese government, motivated by rapidly increasing energy demand and limited oil and natural gas reserves, has promoted policies for energy efficiency and research investments in new energy-saving technologies. At the same time, China has also become home to distinct forms of industrial innovation that often occurs downstream in technology commercialization and redefinition [103–108]. Some evidence suggests that these two themes could be synergistic; that is, despite having less stringent requirements in WTO negotiations [109], developing nations like China that receive large amounts of foreign investment may be able to successfully reduce pollution while contributing to advances in industrial innovation [110].

Given this context, this paper describes how institutional and market forces within an industry (automotive) are associated with the directions of innovation that firms are taking with respect to an emerging technology sector (plug-in vehicles). In this study, we are not interested in *invention*, or the creation of new ideas, but rather *innovation*, or, as Metcalfe & Ramlogan (2008) put it, “a continuous learning process in which firms master and implement the design, production, and marketing of goods and services that are new to them, although not necessarily new to their competitors—domestic or foreign” [111]. In addition, Kline & Rosenberg (1986) emphasize that a successful innovation involves an organization's ability to balance market needs with those of a product's design and manufacturing processes [112]. Thus the market context is an integral component of innovation that also distinguishes it from invention. The context in which firms are innovating will be of central focus throughout this paper.

We seek to derive new theoretical insights into the factors associated with differences in the directions of innovation observed in China's plug-in vehicle sector using inductive grounded theory-building techniques [113, 114]. Our data sources include vehicle sales data, archival data such as news reports, and 37 qualitative interviews with automotive managers and engineers, government officials, researchers, journalists, and industry consultants. We uncover four cases of highly innova-

tive independent domestic Chinese firms developing plug-in vehicles and plug-in vehicle components in China: Chery Automotive, Haike Technologies, Jiayuan Electric Vehicles, and Kandi Technologies. Chery is an independent domestic automaker designing, manufacturing, and selling gasoline and plug-in passenger vehicles; Haike is an automotive transmission start up company developing a low-cost flywheel hybrid transmission; Jiayuan is an independent domestic automaker designing, manufacturing, and selling micro low-speed electric vehicles; and Kandi is an independent domestic automaker designing and manufacturing full electric vehicles for its car sharing service. Since these firms are all innovating in different subsectors of plug-in vehicles, they face different regulatory constraints and target different market segments.

In addition to identifying three distinct directions of innovation (“up”, “down”, and “sideways”) with respect to the frontiers of automotive technology and organizational and business strategies, this study investigates how the historical path dependencies of firms as well as how institutional and market forces might be shaping the wide variety of innovation directions we observe amongst domestic Chinese firms in the plug-in vehicle sector.

5.3 Literature

5.3.1 The Many Types of Innovation in China

China’s rapid economic growth has made it a focal nation for studying innovation and the growing role developing nations are playing in the global production of goods. Scholars disagree on the types of innovation occurring in China. One body of research suggests that China is playing the typical developing nation role in Vernon’s product cycle theory [115] where the most sophisticated and technologically advanced products are invented and initially manufactured in the most industrially advanced nations and later shift their locus of manufacturing to developing nations as product designs are standardized, products become commodities, and competitive advantages become determined by production costs. Recent literature in this vein argues that innovation in China centers around product imitation, cost reduction, and the product development necessary for the scale up and commoditization of products [116–120]. However, an emerging body of literature is now challenging this traditional view, suggesting that China is playing a larger, more complex, and more integral role in the fractured global production of goods where opportunities for adding value are

growing and coming further down stream in the product commercialization process. Research has highlighted how Chinese firms are adding value along the production chain through incremental process innovations [121]. More recently, scholars have argued that Chinese companies are becoming an integral part of the commercialization process of new products [103,106–108]. Some research also shows how Chinese firms are creatively taking advantage of increasingly globalized production environments to catch up and compete with global leaders [104,105].

The studies supporting the traditional product cycle argument suggest that China is trapped in the lowest value segments of global supply chains where new-product innovation is rare. Indigenous Chinese firms in automotive, construction equipment, and machine tool industries have re-engineered focal models of foreign competitors to create products with “good enough” functionality and substantially lower cost, allowing them to slowly gain market share and deepen their technological capabilities but nonetheless remaining at the low-end of the market [116]. Steinfeld (2004, 2010) argues that the ability of global firms to increasingly codify, digitize, modularize, and transmit complex design information has left Chinese firms operating in “shallow networks” where competition revolves around cost cutting rather than innovation [119,120]. Ge & Fujimoto (2004) illustrate how the “quasi-open” architecture of motorcycles manufactured by Chinese firms has paradoxically led them to achieve the largest production volume in the world and yet remain stuck imitating the focal models of Japanese firms. Bottom-up coordination efforts amongst suppliers enabled Chinese motorcycle assemblers to acquire imitated “components transformed as standard parts that can be ordered via catalogues,” which resulted in lowered production costs and new opportunities for parts interoperability but weakened incentives for motorcycle assemblers to conduct long-term R&D [118]. Similar to the network failure of bicycle firms in Taiwan [122] and the “modularity trap” posed by Chesbrough [123], with knowledge about components dispersed amongst suppliers, the Chinese motorcycle assemblers lack the collective knowledge of how to evolve the overall system [118].

Investigations into patenting in China suggest a similar narrative where domestic Chinese firms have struggled to conduct new-product innovation. For example, in recent years large multinational corporations have increasingly established large R&D centers in China due to lower costs there, especially wages of researchers and engineers [124,125]. The majority of U.S. patents granted to inventors based in China and India are owned by non-Chinese multinational corporations rather

than domestic Chinese firms [117]. Thus the rapid rise in domestic patenting over the last decade is more a reflection of an expanding division of labor within international R&D networks than it is domestically driven innovation.

These previous examples of Chinese firms “down marketing” global products suggest that Chinese firms still lag behind the most advanced industrial economies in new-product innovation capabilities. Rather than dispute these claims, other researchers have drawn attention to different types of innovative behavior in China. For example, Ernst & Naughton (2008) describe how Huawei, a giant Chinese information technology company, capitalized on its competitive advantage of lower cost R&D labor to become a leader in the Chinese IT market. Rather than compete at the technological frontier, Huawei combined incremental and architectural innovations to develop integrated communications systems that met the essential needs of operators at lower cost than higher performing mainstream competitors [104]. Modular transformations in the global telecommunications industry have also provided Chinese Integrated Circuit (IC) firms the ability to “source” technological know how and services from Taiwanese semiconductor firms to enter China’s thriving *shanzhai*¹ (no brand) budget smart phone market [105]. Lenovo, one of China’s leading firms in the personal computer industry, has followed a similar development strategy by outsourcing manufacturing to Taiwanese contract manufacturers and focusing instead on attractive designs coupled with strong supply and distribution networks [104]. Huang (2008) attributes much of the success of Lenovo’s strategy to its status as a wholly foreign-invested enterprise originating in Hong Kong, which provided a more liberal regulatory operating space and critical access to capital [126]. These examples highlight new areas where Chinese firms are entering the global production chain and bringing new products to the market.

More recent research has shown how the specialization of Chinese firms in mass production and product commercialization goes beyond incremental innovation. Scholars argue that China is developing an environment of “industrial co-development” [106] through the emerging capabilities of Chinese manufacturers to add value during the process of translating and integrating technology systems [107, 108]. This role makes Chinese firms an integral part of the innovation process in product commercialization and changing China’s comparative advantage as a nation that can

¹山寨: Literally “mountain village” or “mountain stronghold,” the term *shanzhai* refers to the regions where bandits conduct business, far away from official control.

export increasingly high-quality and sophisticated goods [103]. Nahm & Steinfeld (2014) describe “multidirectional, simultaneous learning...as overseas and Chinese firms cooperate to overcome challenges associated with the commercialization of emergent technologies [108],” suggesting that these relationships go far beyond limited views of “inventor” and “manufacturing contractor” towards partners in the innovation process. These scholars argue that this ability of Chinese manufacturers to translate and integrate technology systems for mass production often goes overlooked as an important innovative capability of Chinese firms [103,107,108]. Indeed, Breznitz & Murphree (2011) suggest that it is precisely these innovative capabilities in product commercialization that may be the key to sustainable economic growth for China’s future [103].

Despite this vast literature on innovation in China, the scholarly perspectives still largely suggest that China’s primary role in the global production of goods focuses on process innovations (e.g. Utterback & Abernathy, 1975 [127]) and product adaptations for scale-up, which in many ways strays not that far from Vernon’s original product cycle theory. Together, these previous studies cover extreme ranges in technology and industry maturity, market focus (export-oriented versus domestic Chinese market), and political and institutional support for industries. In this study, we unpack domestic Chinese firm strategies in a nascent market that lacks a global dominant design or technology strategy and which requires innovation for competitive entry: China’s plug-in vehicle sector.

5.3.2 Institutions and Innovation

A large volume of research² has investigated a variety of factors that shape the innovative activity and performance of firms, including market characteristics [129,130], industry dynamics [116,131,132], organizational structure and firm size [133,134], national and regional institutions [1,135–138], resource availability [139,140], and combinations of these [112,132]. Less literature exists on how these dynamics play out in the context of a developing country, and in particular China. Two particularly important lenses for understanding innovation in the context of China are 1) the overlay of regional and national institutions (both formal and informal), and 2) market structure and dynamics.

²Cohen [128] provides a comprehensive review of the empirical studies on factors that influence firm innovative activity and performance.

Institutions, or “the [formal and informal] rules of the game in society” [1] can influence national and regional innovation systems and therewith the innovative performance of nations, regions, and national firms [138, 141–143]. Institutional variation has been used to explain variation in the innovative performance across firms [136, 137], variation in entrepreneurial outcomes [144–146], and variation in the rate and direction of innovation in general [147].

Research has noted differences and conflicting interests between China’s national and regional innovation systems [103]. These tensions can lead to decisions that support local businesses at the expense of national-level plans for industrial upgrading and increased innovative capabilities [148]. Specifically, because local governments are dependent on local businesses for revenues, they sometimes forego riskier, longer-term investments in R&D or technological upgrading in favor of investing in capital-intensive export-oriented manufacturing facilities that attract large amounts of foreign investment and promise faster financial returns [149].

Tensions between local and national incentives need not exclusively be detrimental for innovation; in fact, some argue they have played an important role in developing different and perhaps unexpected types of innovative capabilities. Nahm attributes specialization in technology scale-up and commercialization, or “innovative manufacturing,” to local versus national tensions [107, 108]. National and regional institutional differences may also in certain cases be supporting the development of indigenous innovation capabilities, although the specific capabilities may be different from those the central government anticipated. Research has also shown that private “Township and Village Enterprises” (TVEs) in China’s rural countryside have historically been more entrepreneurial, in particular during the 1980s [126, 150]. In addition, Huang (2008) argues that mainland China has remained successful in achieving economic growth despite internal institutional inefficiencies by accessing neighboring efficient institutions, such as the financial institutions of Hong Kong [126].

5.3.3 Market Structure and Innovation

Finally, it is impossible to consider innovation in China without discussing the size of its market. Characteristics of the targeted market, such as its size [129, 151, 152] and the number of firm or product competitors competing for that sized market [130] can determine firms’ gains from innova-

tion.³ The “replacement effect” argument by Arrow (1962) suggests that firms in more competitive markets have greater incentives to innovate [130]. In the case of the U.S. pharmaceutical industry, Acemoglu & Linn (2003) demonstrate empirically that larger current and future markets have led to increases in innovation [151]. Desmet & Parente (2010) build on this argument, proposing that competition increases in larger markets and also facilitates more process innovations [152]. That said, others argue that the monopolist faces greater incentives to innovate in order to avoid losing existing market power to new entrants [133, 153], and that increased competition can lead to declining R&D intensities [154].

The market in China is large and heterogeneous and exists in the context of a rapidly industrializing nation. Brandt & Thun (2010) suggest that recent shifts in market focus from export-oriented to domestic consumption could be responsible for deepening the levels of technological upgrading amongst domestic Chinese firms as they fight with higher-tech foreign firms to grasp stronger holds in middle market segments. The “fight for the middle” market dynamics encourages domestic firms in low-end market segments to invest in quality upgrading and foreign firms in high-end segments to invest in more localized sourcing and local technology upgrading to bring costs down [116]. In addition to these dynamics, the sheer size of China’s domestic market could be enabling technology upgrading. Altenburg et al. (2008) argue that having a large market has enabled Chinese firms to accumulate more capital and therefore be able to invest more in R&D, hire highly skilled workers, and purchase large amounts of embodied knowledge. China’s market characteristics are also highly attractive for foreign direct investment, which can also facilitate technology transfer and upgrading [129].

Inevitably, institutional and market forces are mutually influential and co-evolve over time. Recent research shows how this coevolution in China may be leading to inefficiencies in technology upgrading in some industries. Brandt & Thun (2016) suggest that regulatory policy that restricts demand within certain market segments can explain observed differences in the levels of technology catch-up between three industries: automotive, heavy construction equipment, and motorcycles. In construction equipment, Chinese wheel loader firms experienced nearly two decades of incubation at the low-end market segment where they were naturally protected from foreign competition, enabling

³Notably, this is not intended to dispute the argument that the size and structure of the market can be socially constructed.

them to incrementally improve their capabilities. However, in automotive the low-end incubation period was much shorter due to earlier regulatory restrictions aimed at market consolidation, which left the market focused on high-end segments controlled by foreign firms through joint ventures with domestic Chinese firms. Competition for low-end segments only came after China joined the World Trade Organization in 2001, by which time foreign firms were already entering lower-end segments and competing with domestic firms. Thus the interaction between policy and demand over time restricted the important market dynamics between domestic (low-end) and foreign (high-end) firms that is needed to foster innovation [131].

5.4 The Joint Venture Institution and the Rise of China's Automotive Industry

Although the accelerated growth rate of China's automotive market did not begin until after entering the World Trade Organization in 2001, China's automotive history goes back over 60 years. Initially nationalist in the 1950s, China gained automotive technology and training from the Soviet Union. After the Sino-Soviet split in 1960, China sealed its auto sector from the outside world for over a decade, a critical period during which "the Europeans, Americans, and Japanese were producing hundreds of thousands of automobiles each year, profiting and 'learning by doing' to increase their innovation capabilities" [155]. After opening to the West in 1972, China's strategy shifted towards importing massive quantities of foreign products and manufacturing equipment in a failed attempt at industrial upgrading. Over the following decade, the inability of Chinese firms to absorb the imported technology signaled the need for a different technology acquisition strategy.

The failures of the 1970s led in the 1980s to the establishment of China's arguably most influential industrial policy strategy: *yi shichang huan jishu*⁴ ("trading the market for technology"). The strategy opened China's vehicle market to the outside world through the Joint Venture (JV) system, which required foreign automobile manufacturers that wished to manufacture and sell vehicles in China to create JV firms with domestic JV parent firms, usually large state-owned enterprises. By limiting foreign firm ownership of the JV to less than 50%, the aim was for the JV to serve as a technology transfer vehicle from the foreign firms to JV parent firms [155–157]. Despite requirements

⁴以市场换技术: This industrial policy prevailed in China from the 1980s through the mid 2000s and is arguably the primary force that has shaped today's market structure in multiple industries.

to share intellectual property, the JV strategy is largely viewed by scholars as a failure in terms of technology transfer [116, 158–161]. Research suggests that the Chinese JV parent firms became technologically dependent on their foreign partners, and many failed to develop independent R&D capabilities.

After a failed attempt in the 1990s to consolidate the fractured automotive industry into a “Big 3 and Small 3” [155, 162], China’s entrance into the World Trade Organization in 2001 opened the flood gates to foreign direct investment through the JV system. Despite fears within China that independent Chinese firms that had arisen during the late 1990s and early 2000s would be crushed by competition from the powerful JV firms, these smaller firms gained a foothold by focusing on the emerging lower-cost small and mini car segments. The resulting market division between foreign JV firms capturing the mid- to high-end segments and Chinese independent and JV parent firms competing for the low- to mid-end segments remains the dominant market segmentation, with foreign and domestic companies fiercely competing for middle market segments [116].

The most recent shift in policy focus has once again returned to domestic independence. In its 2006 medium- and long-term plan for science and technology development, the State Council emphasized *zizhu chuangxin*⁵ (“indigenous innovation”) as the central development strategy for science and technology (S&T) industries. While this effort applies to all pillar S&T industries, the focus in the automotive industry has been characterized by a newfound support for domestic Chinese brands (as compared to previous focus purely on large state-owned JV firms) as well as an extreme push for the domestic development of *xin nengyuan che*⁶ (“new energy vehicles”) which includes PHEVs, BEVs, and fuel cell vehicles (FCVs). Support for these new energy vehicles has led to a multitude of policy experiments from various government bureaus and has largely focused on the development of plug-in vehicles (see section 2.3 of Chapter 2 for a detailed description of the relevant policies.)

⁵ 自主创新: Translated as “indigenous innovation” or “independent innovation,” the strategy (as stated by the State Council) applies to all key science and technology industries.

⁶ 新能源车: Literally “new energy vehicle” as defined by the National Development and Reform Commission to include PHEVs, BEVs, and FCVs.

5.5 Methods

We derive new theoretical insights on innovation in China's plug-in vehicle sector through inductive grounded theory-building, iterating between theory and quantitative and qualitative data [113,114]. Our unit of analysis is firms in China's plug-in vehicle sector. Our analysis explores in particular 1) the emergence of multiple forms of innovation simultaneously occurring within China's plug-in vehicle sector, and 2) the different market, policy, and institutional features that may be working to support or oppose these patterns. Rather than seek causal relationships, our purpose is to build theory. By describing the multiple innovation patterns observed in China's plug-in vehicle sector, we aim to contribute to the ongoing debate on the innovative capabilities of Chinese firms and the interplay between markets, policy, institutions, and innovation in China.

Our analysis rests on three data sources: vehicle sales data, archival data such as news reports, and semi-structured interviews. Since vehicle sales figures are reported by the firms themselves, we collected firm level vehicle sales data by make and model from 2003 to 2014 from two different sources for comparison: 1) Automotive Industry Yearbooks published by the Chinese Association of Automotive Manufacturers (CAAM) [163], and 2) the automotive website gasgoo.com [164]. Since the automotive yearbooks are only published in print, the data were hand-copied. We used a custom-built web scraper in Python to collect sales data from gasgoo.com to verify the automotive yearbook sales. These data largely agree between the two sources with only small variation between a few firms, none of which differ on order of magnitude at the annual level. Aggregated sales totals by manufacturer and brand also match those reported by the China Passenger Car Association. We also examine over thirty news reports on China's plug-in vehicle sector as well as over thirty domestic Chinese scholarly publications on domestic Chinese automotive firms and innovation in China.

In addition, we conducted 37 semi-structured interviews between May 2014 and July 2015 with a variety of stakeholders in China's plug-in vehicle industry, including managers and engineers at automotive firms (including JV, JV parent, and independent firms), university researchers, non-profits, government experts, consultants, and reporters. Interviewees were contacted through a combination of a snowball technique (previous interviewees introduced future interviewees) and cold-calling different sources. Table 5.1 below summarizes the full set of interviews. The goal of

these interviews was to uncover what innovation, if any, was occurring in China’s plug-in vehicle sector, and what factors might be supporting or hindering the observed innovative outcomes or lack thereof.

Table 5.1: List of interviews by type and position

Case Study Firm	Organization	Position	Interviews
	JV Auto Firm	Manager	7
	JV Auto Firm	Engineer	3
Chery	Independent Auto Firm	Founder	1
	Independent Auto Firm	Manager	4
	Independent Auto Firm	Engineer	5
Haike	Independent Auto Firm	Co-Founder / Engineer	1
	Independent Auto Firm	Co-Founder	1
Jiayuan	Independent Auto Firm	Founder / CEO	1
	Independent Auto Firm	Engineer	1
Kandi	Independent Auto Firm	Manager	2
	Consulting Firm	Consultant	2
	Government	Analyst	2
	Non-profit	Consultant	2
	Non-profit	Researcher	1
	University	Researcher	3
	News Outlet	Reporter	1

5.6 Results

5.6.1 Independent Chinese Firms Are Leading China’s Plug-in Vehicle Market

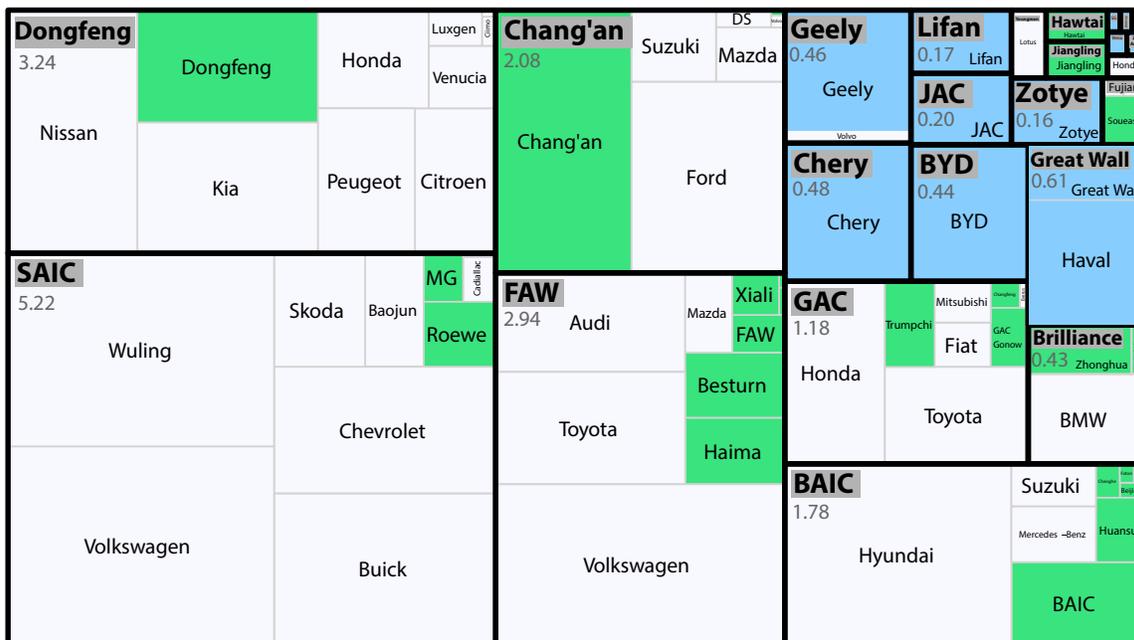
We first examine the vehicle sales data collected on all passenger cars and plug-in vehicles sold in China in 2014. The box sizes in Figure 5.1 illustrate the relative market share by manufacturer and brand and the color indicates which type of firm the sales belong to: JV, JV parents, or independent. Of the approximately 19.7 million passenger vehicles sold in 2014, the vast majority were sold by JV firms, which collectively sold 13.9 million vehicles (70.6% of the market). JV parent firms sold 3.2 million (16.2%) and independent firms sold 2.6 million (13.2%). In contrast, independent firms dominated sales within the plug-in vehicle market, selling 46,843 (87%) of the 53,827 plug-in vehicles sold. JV parents firms sold just 6,402 (12%) and JV firms sold only 582 (1%).

The contrast in market shares by different firm types between all vehicles and just plug-in vehicles is striking. Most prominent is the lack of plug-in vehicle sales by JV firms given their dominance in the conventional gasoline vehicle market. Our interview data revealed several factors that have likely led to this situation. First, the JV firms have followed the technological and development strategies of their foreign partners. By licensing and selling relatively older traditional vehicle technologies from their home markets, these foreign firms have been able to maintain high prices and make record profits through their JV firms, even after splitting profits with their JV counterparts. As one former JV firm manager said, “*Selling gas cars makes money! The business case [for EVs] is weak. Margins [for CVs] in the west are only 3-5%, but in China they’re around 10%!*”⁷ In contrast, foreign firms perceived bringing their most advanced electrified vehicle technologies to China (along with necessary global suppliers) at large scale as exposing themselves to unnecessary risk. Participation in a JV requires that foreign firms share intellectual property with their JV partner firms who could later become competitors. In addition, to receive subsidies they would have to domestically source one of the “three longitude” core technologies (batteries, motors, or battery management systems). Focusing on an established product line with an established supply chain in traditional vehicles is a more conservative strategy that has resulted in high profitability and lower uncertainty.⁸

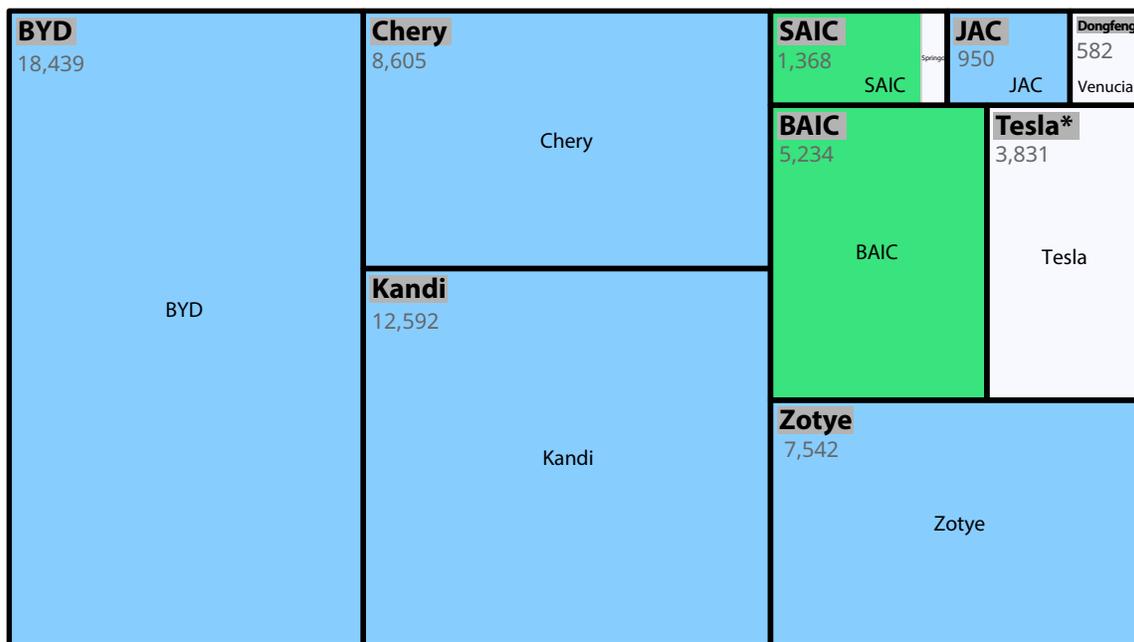
⁷Interview 7.

⁸Interviews 1, 2, 7, 9, 10, 13.

2014 Passenger Vehicle Sales in China (Total = 19.7 million)



2014 Plug-in Vehicle Sales in China (Total = 59,143)



*Imported

Box size indicates market share

Firm Type

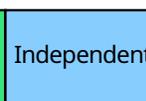
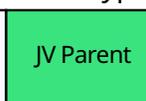


Figure 5.1: 2014 all passenger vehicle sales (top) and plug-in vehicle sales (bottom) in China by manufacturer and brand (sales in top figure given in millions).

Of the few plug-in vehicles produced by JV firms in China, many are simply low volume demonstrations to meet a government requirement. For example, some local governments have restricted land rights to expand JV firm manufacturing facilities unless it produces a plug-in vehicle. To meet these demands, they often retrofit a few hundred existing conventional vehicles with an electric drive train. Since these plug-in vehicles are manufactured in low volume (and often by hand), they are extremely costly and often sold at a loss (even with subsidies) as taxi fleets rather than to private consumers. Such maneuvering has enabled the global automakers to, as one former JV manager put it, “*check the box*”⁹ on making plug-in vehicles while continuing to expand their businesses in conventional gasoline-powered vehicles.¹⁰

The lack of JV involvement in the Chinese plug-in vehicle sector has left market opportunities to Chinese automakers, both JV parent firms and independent firms. Between the two types, the independent firms have captured much larger market shares relative to JV parent firms in the plug-in vehicle market. Independent firms have now had over a decade to learn and develop R&D capabilities, whereas JV parent firms have heavily relied on their foreign partners for technical know-how, focusing their R&D efforts on adapting foreign technologies to Chinese consumer preferences rather than conducting ground-up product development. In addition, past research has also shown that foreign automakers have greatly limited the transfer of technology and know-how to their Chinese JV parent firm counterparts [20, 159].

5.6.2 Independent Firms Are Innovating in Different Directions

Our in-depth interviews revealed four examples of independent Chinese firms within China’s plug-in vehicle sector with extraordinarily different forms of innovation: Chery Automotive, Haike Technologies, Jiayuan Electric Vehicles, and Kandi Technologies. In focusing on these four firms, our intent was not to identify a representative set of all independent domestic firms but rather illustrate the range of observed innovative activities. These firms span multiple business strategies, including manufacturing and selling whole vehicles (Chery and Jiayuan), manufacturing and selling vehicle components (Haike), and manufacturing and renting vehicles (Kandi). Two of these firms (Chery and Kandi) each have sizable portions of China’s plug-in vehicle market share (see Figure 5.1) while

⁹Interview 13.

¹⁰Interview 2, 7, 9, 13, 14.

Haikē and Jiayuan are still in start-up phases. Table 5.2 summarizes the four firms' history, technology, and current outputs. For each firm, we discuss its historical evolution and the interaction of that history with the firm's innovation direction in China's plug-in vehicle sector.

We observe three distinct directions and describe them as innovating up, down, and sideways. Firms innovating "up" are those that advance the technological frontier to enter new markets; firms innovating "down" are those that combine or redefine older technologies in innovative ways to enter new markets; and firms innovating "sideways" are those that combine technology with new organizational and business strategies to enter new markets. Figure 5.2 shows how our four case study firms align with these innovation directions.

Table 5.2: Overview of case study firms

	Chery	Haikē	Jiayuan	Kandi
Flagship EV Product	<i>eQ</i> BEV	Flywheel Hybrid Transmission	<i>Lingzu</i> LSEV	BEV Car Share Tower
Year Est.	1997	2012	1982	2012
Ownership & Funding	Wuhu Gov't	Private Investors	Private (Crowd-sourced)	Private Investors (KNDI)
Tech. Origins	Auto parts	Formula Racing	BEVs	Batteries, CVs, BEVs
Products	CV, BEV, PHEV	Flywheel Hybrid Transmission	LSEV, BEV	BEV, Car Share Service
2014 Domestic Sales	357,585 CVs, 8,605 BEVs	NA	NA	BEV Car share: Hangzhou (20k), 9 other cities (14k), BEV Sales: 11k
2014 Exports	108,238 CVs	NA	500 BEVs	NA
2015 Milestones	5,337 BEVs Jan. – Jun.	Begin pilot production	Obtain license, begin LSEV sales	20k BEV sales, car share in 9 cities

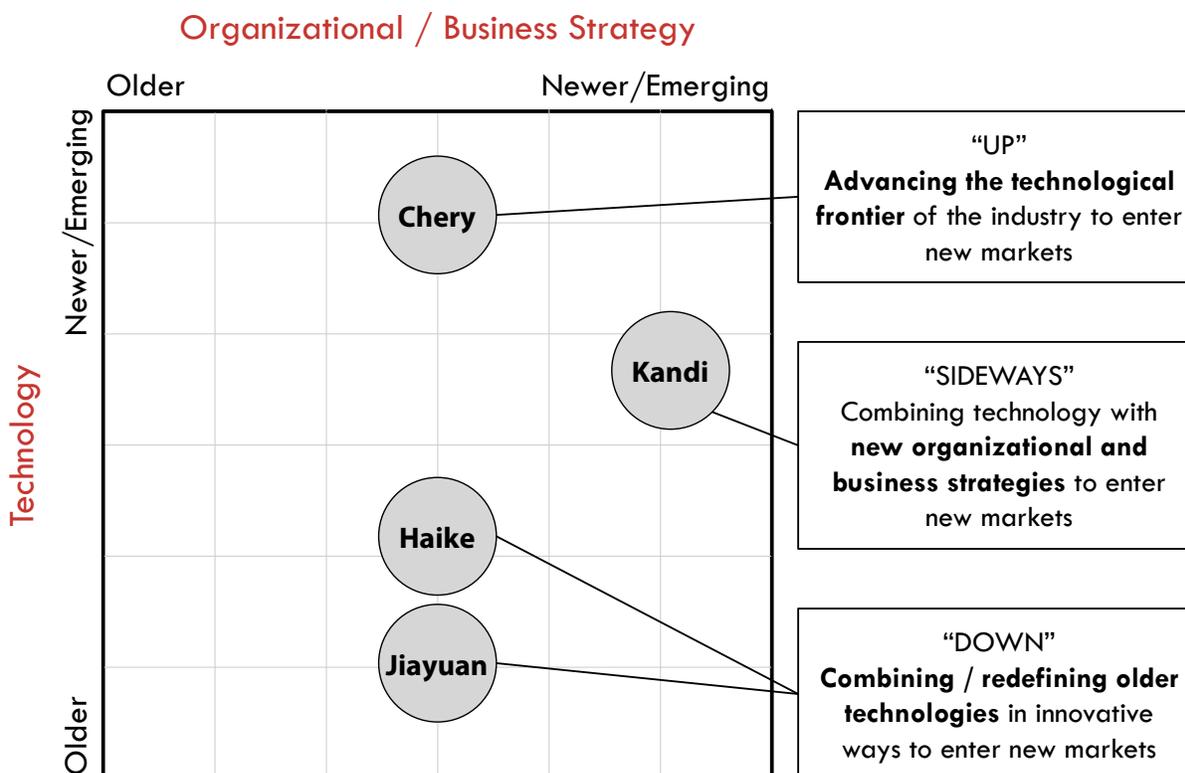


Figure 5.2: Case study firms innovating in different directions: Up, Down, and Side-ways.

5.6.3 Chery Automotive

脚踏实地: “Stepping on Solid Ground”¹¹

Historical Evolution: From Leveraging Local Connections to Developing Technical Capabilities by Learning by Doing and Hiring

Chery was founded on January 8, 1997 as Anhui Automotive Part Industrial Company (AAPIC) with a registered capital of 4.8 billion Yuan, headquartered in Wuhu, Anhui Province. Their first engine assembly line, an outdated British Ford line, was purchased in 1996 for \$25 million and construction of their first engine plant began in March 1997. Against the will of the central government (which at that time strictly regulated entry into the automotive industry), the local Wuhu city government supported Chery’s growth as a vehicle manufacturer in an effort to grow the local industry. Without a license from the central government, Chery illegally began producing vehicles in 1999, and since they could not be sold elsewhere, the Wuhu government required local

¹¹The Chinese idiom *jiao ta shi di* literally means “to step on solid ground”; figuratively, the phrase means working hard and focusing on the fundamentals will lead to steady, continual improvement.

taxi fleets to purchase them. After discovering this, the central government ordered Chery to shut down. To maintain legitimacy, Chery partnered with Shanghai Automotive (SAIC) to use their license, giving up 20% ownership to SAIC and re-naming the firm “SAIC-Chery Automobile Company.” After acquiring its own production license, Chery broke ties with SAIC in 2003 to regain independence, allegedly over a dispute with SAIC’s partner GM around the Chery QQ, a nearly identical copy of the Chevrolet *Spark*, a model GM had purchased from South Korea’s Daewoo [165–167].

Chery has since grown into one of China’s largest independent automakers with six domestic production plants and 15 complete knock down plants¹² in developing nations around the world. From 2003 to 2011, annual sales grew from approximately 90,000 to 630,000. They independently design their vehicles, and their company culture is characterized by a sense of pride in being a Chinese company making Chinese cars.

Chery’s technology capabilities evolved in a similar manner to many indigenous Chinese firms, transforming from a technology *imitator* to a technology *integrator* with a strong R&D force. Chery facilitated this evolution by conducting joint R&D projects with leading automotive suppliers and consultants and aggressively hiring talented, experienced engineers and managers from international automakers and suppliers. Today, its R&D force of over 6,000 engineers conducts ground-up vehicle design for conventional, hybrid, and plug-in vehicles.

Rather than simply outsourcing design work to automotive suppliers, Chery used its relationships with global auto suppliers as conduits for gaining technical skills and know how. As one assistant manager to the president put it, “*The most important thing is doing it...learning by doing is the path to doing it on your own.*”¹³ For example, Chery jointly developed its first engine brand with self-owned intellectual property rights, the ACTECO engine line, by hiring the famous Austrian engine firm AVL. From 2002 to 2008, their collaboration evolved from one where AVL served as “master,” managing product development timelines and conducting R&D primarily in Austria, to “consultant,” where most R&D was managed and conducted within Chery’s automotive R&D center in Wuhu with AVL supplying technical assistance when needed [165]. The collaboration produced 3 engine designs developed for 18 vehicle models. During that same period, Chery’s

¹²Complete knock down plants assemble vehicles using kits that contain every component needed for assembly.

¹³Interview 15.

R&D grew from approximately 500 engineers to nearly 3,000 [166]. Other examples of successful collaborations include their first hybrid vehicle developed with British automotive consulting firm Ricardo in 2006, leading Chery to be the only Chinese automaker to showcase a hybrid vehicle in the 2008 Beijing Olympics.¹⁴ The project resulted in two hybrid technologies: an integrated starter generator and a belt-driven starter generator, which are reported to reduce fuel consumption by 32% and 7-10% compared to Chery's conventional vehicles. Chery has also co-developed exterior designs with Italy-based Pininfarina, designers for Ferrari, and Bertone, designers for Lamborghini.

In addition to learning from international suppliers, Chery has acquired skills and know how by aggressively hiring experienced technical experts and managers in the automotive industry. Many of Chery's early engineers came from the R&D centers of large state-owned enterprises (the Chinese parent firms of foreign JV firms). Since the foreign half of the JV firms conducted the majority of technical R&D, the underutilized Chinese engineers at the JV parent firms were eager to join Chery to take on the challenge of independently developing Chinese vehicles. Even Chery's president and CEO, Tongyao Yin, was a 12 year veteran and star engineer at FAW as manager of the FAW-VW *Jetta* plant [166]. Over 100 FAW workers left to join Chery to develop the *A11 "Fengyun,"* Chery's first model, a variant of the SEAT *Toledo* based on the VW *Jetta*. Much of the R&D work for the three initial models released in 2003 was done by engineers from Dongfeng (another large state-owned automaker with whom Volkswagen shares a joint venture) in an automotive design and development company founded by Chery called "Jiajing Technology Company," of which the engineers themselves owned a 20% stake.

In addition to hiring former JV employees, Chery also aggressively hired "sea turtles,"¹⁵ a term used to describe highly talented Chinese engineers and managers who left China in their youth to study or work abroad before returning to China later in life bringing deep technical and managerial know how (often with 20 or more years of experience). Sea turtles are often hired as high-level managers. For example, Ming Xu, who worked for Visteon in Detroit, was hired in the early 2000s as director of Chery's R&D center [166]. Some of these sea turtles, the so-called "*Qianren*,"¹⁶ which a former senior engineer at Chery referred to as, "*secret weapons*," were actually given 1 million

¹⁴Interviews 16 and 17.

¹⁵The name refers to the fact that sea turtles always return to their home beach where they were born to reproduce after living a long life away at sea.

¹⁶千人: Literally "Thousand Person," the term means people who have a "thousand" talents or capabilities—a very experienced or senior-level engineer or manager often with a highly technical background.

RMB by the central government after an extensive application in exchange for returning to China to help domestic Chinese firms.¹⁷ These individuals proved critical when making decisions on where to focus technical efforts and prioritizing what problems to solve in order to achieve rapid timelines to the start of production.

Innovating “Up” with BEVs

In addition to Chery’s success in developing conventional vehicles, Chery is also one of the few firms in China mass-producing and selling an independently developed BEV. Chery began its first electric vehicle project in 2001, the same year it officially received an automotive production license. When just 4 years old, the firm received a 100,000 RMB research grant from China’s 863 national R&D program administered by the Ministry of Science & Technology to conduct R&D on electric vehicles.¹⁸ Since then, Chery has been continuously awarded grants from the central government to support its plug-in vehicle development. With the success of previous alternative drive train vehicles such as the hybrid vehicle developed with Ricardo, Chery began developing a BEV project (the S18) in 2006, which resulted in the Riich *M1* BEV that went on the market in 2010.¹⁹

Targeting city people who only need a simple car, Chery has focused on making a smaller, affordable BEV that would be priced with other smaller cars (under 100,000 RMB, after subsidies). To achieve lower costs, Chery has developed a common platform for their *eQ* BEV and *QQ5* conventional gasoline vehicle that share components, including the chassis. They also follow the Toyota Production System, employing a mixed production line and integrating BEV assembly into the same line with gasoline vehicles to utilize existing plant capacity, enabling higher economies of scale in the production of many components despite low overall BEV volumes. The combination of common platform designs with flexible use of production lines has enabled Chery to develop and deliver a serious BEV. While high battery costs from two different Chinese suppliers still make the BEV *eQ* more expensive than similarly sized conventional vehicles, current subsidies bring the price down to under 100,000 RMB (USD\$15,000) and even lower in some cities with the addition of local subsidies. For comparison, Chery’s gasoline-powered *QQ* sells for 40,000 – 55,000 RMB (USD\$6,000 - \$8,300).

¹⁷Interview 33.

¹⁸Interview 23.

¹⁹Interview 18.

5.6.4 Haike Technologies

大巧若拙, 大道至简: “Dumbing Down is the Way Up”²⁰

Historical Evolution: Redefining and Commercializing Technology for China’s Market

Haike Technology is a hybrid transmission startup firm founded in 2012 based in Changzhou, Jiangsu Province, about 100 miles northwest of Shanghai. Although the startup has just 15 employees, nearly all came from senior level engineering positions and have Ph.D. degrees, and 4 of them are *qianren* sea turtles. For comparison, Haike has more *qianren* sea turtles than many of the large state-owned enterprises that have thousands of employees.²¹

Haike is commercializing a hybrid transmission that uses a mechanical flywheel and electric motor to recover energy losses during vehicle braking. When decelerating, the transmission transfers the vehicle’s kinetic energy to a heavy flywheel, spinning it up to a high rotation per minute. The flywheel keeps spinning while the vehicle is stopped, and then during acceleration energy is transferred from the flywheel back to the transmission to power the wheels, accelerating the vehicle without use of its engine. The system is capable of achieving similar energy savings to those of more common hybrid vehicles such as that of the Toyota *Prius*, which uses an electric motor and battery to reduce fuel consumption by as much as 30% compared to conventional gasoline vehicles, but the flywheel does it at substantially lower cost (as much as 50% less than a conventional electric hybrid).

In addition to improving conventional vehicle fuel consumption, this technology can have a major impact on plug-in vehicles. Because a kinetic energy storage system removes the need to rapidly and frequently charge and discharge a plug-in vehicle’s battery pack during acceleration and deceleration, it reduces the required number of battery cells to drive a fixed range and elongates battery life by reducing the temperature spikes, which in turn reduces the requirements on the battery cooling and management system. Since the batteries remains the most expensive component of plug-in vehicles, smaller and simpler battery systems can dramatically reduce the overall vehicle cost.

²⁰The Chinese idiom *da qiao ruo zhuo, dadao zhijian* means intelligent people often seem slow-witted. Haike’s founder used the phrase to describe their commercialization strategy of “dumbing down” to meet market needs.

²¹Interview 26.

Early applications of the flywheel hybrid technology were originally developed for large stationary energy storage used in accelerating and decelerating light rail systems. In 1991, Chrysler developed an early vehicle application in a racing hybrid called the *Patriot* that utilized a flywheel as an energy storage device. During the 1990s, concerns over safety ultimately led to western governments, including the United States and England, refusing to grant research funding on the technology in favor of focusing instead on battery technology for energy storage.²² The primary concern was the ability to safely control the extreme amounts of energy stored in the spinning flywheel that, as one of Haike's engineers put it, "...was like taming a wild animal...and if it gets out of control it could kill people."²³

Frustrated with the lack of support for the technology in the west, Haike Technologies founder, Dr. Frank Liao, brought the idea to China along with the technology's inventor and patent holder from the U.K., Chris Ellis, to commercialize it for China's vehicle market. Dr. Liao is a *qianren* sea turtle with over 20 years of experience in automotive engineering in the U.S. During the 1990s he worked on the first generation of the GM *EV1* (an early BEV) and conducted a series of clean energy automobile projects with the U.S. Department of Energy. His initial attempt to introduce the technology to Beijing Automotive's New Energy Vehicle department, where Dr. Liao was serving as chief technology officer, failed as the Beijing Automotive's leadership sought different technology directions.²⁴

Confident in the technology, Dr. Liao looked to the favorable environment in Changzhou to establish Haike New Energy Technology as a new high-tech startup. While discussing the decision to locate their headquarters in Changzhou, one of Haike's senior managers said, "*When I first went to Changzhou, I noted the strange level of support at the full levels [of government]—high-level, the mayor, etc.—and how interested they seemed to be in what we were doing. Not just us, but the other players...each city retains something like 30 percent of all the tax revenue generated in the city...so the cities do have the freedom to back the winners they choose.*"²⁵ Haike Technologies rent their pilot production plant from the Changzhou government at a highly reduced rate and also have been given free office space from which to run their business in the startup phase.²⁶

²²Interviews 26 and 34.

²³Interview 26.

²⁴Interview 33.

²⁵Interview 34.

²⁶Interview 26.

Innovating “Down” with Flywheel Hybrid Transmissions

Although the technology origins of Haike’s flywheel hybrid transmission dates back to the 1990s, the technology has never been commercialized for the passenger vehicle market and is exclusively used in Formula racing. In order to bring the technology to China’s passenger vehicle market, Haike engineers are balancing tradeoffs between performance, reliability, safety, cost, and a rapid timeline from design to mass production. The goal is not to develop a flywheel hybrid system comparable to those used in racing but rather a simple and less expensive system that can achieve similar energy savings to traditional electric hybrids but at substantially reduced cost. As a result, rather than spend resources developing complex individual components like the flywheel itself, Haike is focused on designing a simple, low-cost system architecture to quickly develop a commercially ready product for China’s domestic market.

Haike’s flywheel design provides a good example of the types of tradeoffs Haike engineers are making. Existing flywheel technologies used in racing reach high rotational speeds (on the order of 50,000 rotations per minute) to maximize energy storage capacity. However, the complex manufacturing processes and lack of established reliability associated with these designs has made them a challenge for mass production and safety over the product’s lifetime. Instead, Haike is using a much simpler metal flywheel with a lower rotational speed (just 20,000 rotations per minute) and coupling it with an electric motor for precision control. This choice still stores an adequate amount of energy but enables a simpler, safer, and highly reliable design that is less expensive to mass produce. Dr. Liao described this type of design decision with a Chinese idiom: “*da qiao ruo zhuo, dado zhijian,*” meaning “dumbing down is the way up.”²⁷

Another key aspect of Haike’s development process is to avoid reinventing the wheel. A crucial component to successfully and safely controlling the flywheel is the planetary gearing system originally developed by Toyota for their electric hybrid drive trains. For their first prototype, Haike engineers worked for a year with a strategic alliance of Chinese suppliers to reverse engineer components that provide the same functionality as the Toyota planetary gear system without infringing on Toyota patents. Having now mastered the production of all necessary components (a list of around 50-60 individual parts), Haike can now independently produce both the flywheel and their

²⁷Interview 26: “大巧若拙，大道至简。”

own planetary gearing system to control it. Efforts like these have enabled Haike to rapidly build prototypes of their design by learning from the innovations of others.

5.6.5 Jiayuan Electric Vehicles

存在就是合理的: “If It Exists, It Must be Reasonable”²⁸

Historical Evolution: Licensing and Delayed Market Entry

Jiayuan Electric Vehicles is a market-driven firm headquartered in Nanjing, Jiangsu Province, with an established history in designing and selling BEVs. Jiayuan is a father-son business. The CEO’s father, Professor Li of Zhengzhou University, began developing BEV motors and controllers in the 1970s. After studying automotive design and engineering at a Zhengzhou technical school, his son returned home to found Jiayuan, primarily to earn money to fund his father’s research. During the 1990s (a time when global automotive firms such as GM and Toyota were also experimenting with BEVs), Jiayuan expanded and began developing a number of BEVs, ranging from small sedans and SUVs to mini buses. During this period, obtaining an automobile manufacturing license from the central government to domestically sell vehicles required proof of billions of RMB in investment and the ability to produce conventional gasoline vehicles. Unable to meet these requirements, Jiayuan was limited to exporting their BEVs, primarily to Europe. In the 2000s, Jiayuan explored other domestic markets that did not require an automobile production license, such as electric sightseeing buses for tourism. In 2012, Jiayuan began developing a new BEV aimed at a new burgeoning domestic market—*disu diandong qiche*²⁹, or “low-speed EVs” (LSEVs).

The LSEV market is by far the fastest-growing segment in China’s plug-in vehicle market, selling an order of magnitude greater in volume than highway-ready plug-in vehicles (427,000 LSEVs in 2014 compared to just 49,000 BEVs and 30,000 PHEVs). A typical LSEV is a 4-wheeled, low-priced BEV with a maximum speed of less than 80 km/h and a limited range of around 50 – 80 km. These vehicles use older technologies, such as lead acid batteries, to keep cost down and sell for as low as RMB 30,000 (< USD\$5,000). Firms entering the LSEV market vary widely in their technical, engineering, and design capabilities, ranging from rural farmers with limited

²⁸The Chinese idiom *cun zai jiu shi heli de* can be translated as “what is rational is real, and what is real is rational,” meaning that if it exists then it must be reasonable. The phrase is also often used to describe the current regulatory approach to LSEVs.

²⁹低俗电动汽车: Literally translates to “Low speed electric vehicle.”

manufacturing experience to firms with decades of experience in plug-in vehicle development. Many (if not all) of these vehicles do not fall into any particular regulatory category for motor vehicles, and as a result most can be operated without a license plate or even a driver's license, streamlining their rapid adoption. They are usually limited to local roads and restricted from highway use. Due to their rapid sales, local governments are simply allowing them to be bought, sold, and operated without regulatory oversight. One senior engineer at Shanghai Automotive used a Chinese idiom to explain the government's view towards LSEVs: "*cun zai jiu shi heli de*," meaning "if it exists, then it must be reasonable."

LSEVs are particularly popular in two areas: rural towns (in particular in Shandong province) and in inner cities. The relatively low incomes, lack of gasoline infrastructure, and broad availability of electricity in China's rural areas make LSEVs well suited to meet the needs of farmers and other rural citizens. In urban centers, vehicle ownership can be onerous and expensive, even with higher incomes and abundant fueling stations. Many large, Tier I cities restrict driving in certain areas to only every other day and limit vehicle registrations with monthly caps, employing lottery or auction systems to distribute license plates. In Shanghai, for example, license plates can be auctioned for as much as 100,000 RMB (USD \$15,600), higher than the price of many cars. Since LSEVs do not require license plates (at least for now), they are a popular option for city dwellers that want personal mobility but cannot afford the price or hassle of owning a conventional gasoline vehicle.

Innovating "Down" with Low-Speed EVs

By combining existing technologies in a new way, Jiayuan is capitalizing on their years of experience designing BEVs and entering the emerging LSEV market with an attractive 2-seater, the *Lingzu*, aimed primarily at urban centers rather than rural towns. With attractive features, such as a large flat-screen display with navigation, air conditioning, and power windows, Jiayuan's *Lingzu* fills the gap between the discomfort of a bicycle or e-bike (especially in bad weather or heavy pollution) and the expense and hassle of owning a conventional gasoline vehicle. Jiayuan is also not only focused on China's domestic market. Their LSEV was intentionally designed to be 2.2 meters long to maximize how many can be fit into a standard international shipping container and 1.2 meters wide to be able to fit between standard sidewalk and bike lane barriers.³⁰

³⁰Interview 32.

Perhaps one of the most interesting aspects of Jiayuan is their funding structure. Jiayuan used crowdsourcing to raise 20 million RMB (USD\$3.1 million) to construct its pilot production facilities. Calling their structure a “McDonalds model,” early investors can later operate their own small franchised manufacturing facilities and sell their own Jiayuan LSEVs. Thus rather than offer investors stock options, they instead are given full franchises, from manufacturing to sales, leaving the parent firm’s responsibility to only new product development.

5.6.6 Kandi Technologies

异曲同工: “Different Tune, Equally Melodic”³¹

Historical Evolution: Right Place at the Right Time

Kandi Technologies is a relatively new BEV firm founded by chairman and CEO Xiaoming Hu in 2007 and headquartered in Hangzhou, approximately 110 miles south west of Shanghai. Prior to founding Kandi Technologies, Chairman Hu had over two decades of experience in China’s automotive industry, climbing the ladder from engineer to top-level management. He served as the General Manager of the Yongkang Vehicle Company, the Wanxiang Electric Vehicle Developing Center, and the Wanxiang Battery Company—the Chinese firm that purchased American lithium ion battery manufacturer A123. From 2003 to 2005 he served as the chief scientist and project manager for the Wanxiang Pure Electric Vehicle Development project funded by the 863 National High-Tech R&D program. With his deep technical and managerial experience in the BEV industry, Chairman Hu developed a vision for China’s BEV industry focused on solving the infrastructure and business model challenges associated with BEVs.

Originally manufacturing go-karts and all-terrain vehicles, Kandi Technologies began manufacturing BEVs in 2012 with a strategic plan to operate a car sharing rental service. The traditional model of selling BEVs has faced several important barriers to adoption in China, such as high prices (primarily due to high battery costs) and a lack of parking and charging availability. While the central government has attempted to overcome the former challenge with heavy subsidies, the latter remains unsolved since most city dwellers live in high-rise apartments and are limited to street parking or underground garages. As a result, owning and operating a BEV remains impractical in

³¹The Chinese idiom *yì qū tóng gōng* literally translates as, “Different Tune, Equally Melodic.” Figuratively, the idiom means different approaches can also lead to equally satisfactory results.

many Chinese cities since fully charging a BEV can take as much as 10 hours or more, depending on the battery capacity and charging rate.

Kandi's success has deeply relied upon the support of local governments as well as the state-owned State Grid Corporation of China, China's largest power supplier. In fact, considering Hangzhou's extensive history of experimenting with EVs projects, it is no surprise that Kandi chose it as its headquarters. In 2005, the Hangzhou Government began assessing the viability of EV demonstration programs. In 2006, the Hangzhou Power Authority began constructing charging stations for EVs. In 2009, Hangzhou was selected by the central government as one of the "Ten Cities, Thousand Vehicles" EV demonstration cities, allocating subsidies to EV buyers in Hangzhou. In April 2010, State Grid was mandated by the central government to invest in EV charging infrastructure for Hangzhou, which was selected as State Grid's EV Business Pilot Model City.

Kandi's origins can also be traced back to earlier EV projects in the city of Hangzhou. In 1999 (before the central government began supporting EVs), the Zhejiang Provincial government established the Zhejiang Electric Car Project Working Group, which in 2002 was inherited by the Zhejiang Wanxiang Electric Vehicle Development Center. The center received funding from the national 863 high-tech research program to develop four electric vehicle projects. Chairman Hu led the first of these projects in 2006, one year before founding Kandi. The projects at Wanxiang set clear development goals centered on using a battery swap system to avoid a costly charging infrastructure build out in the city and region. With the strong support received from the Zhejiang Provincial government, the Hangzhou City government, and the Zhejiang Electric Power Grid Company, Chairman Hu had the backing needed to implement the ideas developed at the Wanxiang EV Development Center into a BEV startup [168]. Some of the center's research can directly be seen in Kandi today, such as the vehicle swap system (based on the battery swap system) as well as a patented side-loading battery swap system in Kandi's *K10* two-seater BEV. In 2011, Kandi was awarded a contract to lease 20,000 of its BEVs in the city of Hangzhou as a pilot car sharing program. In addition to subsidies received by the central government in the amount of 60,000 RMB (U.S.\$9,400) per BEV, the Hangzhou Government also provided 800 million RMB (U.S. \$126 million) in subsidies to purchase the cars.

Innovating “Sideways” with BEV Car Sharing

Rather than attempt to improve BEV technology, Kandi is overcoming BEVs’ high price and infrastructure challenges by using existing BEV technologies and innovating on the business model and infrastructure around it. Kandi has created its “Micro Public Transit” car sharing rental service that offers small two-seater BEVs for hourly rental or long-term lease. Since the firm manages the high battery costs associated with BEVs, customers are offered low rental prices of just 20 RMB per hour (U.S. \$3.25/hour). Perhaps their most interesting innovation is the towered vehicle “vending machines” Kandi has developed to vertically store and charge their BEVs, solving both problems of parking availability and long charging times. Customers low on charge can simply swap their BEV for a freshly charged one by driving to the nearest charging tower. By shifting focus away from developing vehicle technology and instead developing business model, infrastructure, and software innovations, Kandi is taking a different pathway to introduce BEVs into the market.

In addition to Kandi’s local success in Hangzhou, demand for car sharing services should not be expected to slow down. In 2014, the city of Hangzhou followed the precedent set by Beijing and Shanghai by announcing it will restrict annual vehicle sales to just 80,000 [169]. As other cities follow suit in China’s efforts to reduce pollution, car sharing services and other alternatives to car ownership are likely to grow.

5.7 Discussion

The four case studies illustrate a sample of the large variety in innovative behavior among independent Chinese firms in the plug-in vehicle sector. Some of this diversity could be explained by the fact that plug-in vehicles are an emerging industry that has not yet reached a “dominant design” (Utterback, 1994), motivating firms to experiment in different ways [170]. Nonetheless, the lack of a dominant design may not by itself go far enough to explain the sustained, simultaneous growth of a variety of innovation directions in plug-in vehicles in the shadow of the largest market in the world for the dominant design in the automotive industry (i.e. the conventional gasoline car). For contrast, innovation in the plug-in vehicle sector in the U.S. has largely been in the “up” direction with a focus on advancing the technological frontier.

These observations suggest that there may be something different about China’s market and

innovation environment that could lead to this diversity of innovation within one sector. Based on our interview data, we hypothesize that the complex co-evolution of institutional and market forces in conjunction with the individual historical path dependencies of firms in China’s automotive industry has created an environment of constraints and incentives that have encouraged the observed variety of innovations to emerge from independent domestic Chinese firms in the plug-in vehicle sector. In particular, we theorize that three characteristics of the Chinese institutional environment help explain the observed diversity: 1) national institutions, such as the written JV licensing regulatory requirements as well as local content requirements, that have inadvertently removed foreign competition, 2) local institutions, such as extreme protectionism at the local or regional level, that have supported the incubation of a diverse set of innovations, and 3) a large, heterogeneous national market with enough demand to enable these innovations to co-exist. Table 5.3 summarizes the role of national institutions, local institutions, and market characteristics for each case study firm.

Table 5.3: Summary of institutional and market forces for case study firms

	Chery	Haikē	Jiayuan	Kandi
Innovation Direction:	Up	Down	Down	Sideways
Products:	Majority: CVs, SUVs; Minority: Small BEVs	Low-cost hybrid transmissions	Majority: LSEVs; Minority: BEVs	Majority: BEV car share; Minority: Small BEVs
Organizational / Business Strategy:	Manufacture & sell vehicles	Manufacture & sell vehicle transmissions	Manufacture & sell vehicles	Manufacture, rent, and sell vehicles
National Institutions:	No foreign PEV competition; design for regulation	No foreign competition	Licensing delayed entry	No foreign PEV competition
Local Institutions:	Protection while transitioning from parts to automaker	Free office space, low pilot production rent	Regulatory gray area allowing local adoption	Strong relationship with Hangzhou city
Markets:	Simple, affordable cars priced under 100k RMB	Hybrid transmissions	In between e-bikes and gas cars (urban & rural)	In between e-bikes and gas cars (urban)

5.7.1 Removing Foreign Competition: The (Inadvertent?) Bait and Switch

While the formal JV institution was originally implemented to facilitate the transfer of foreign conventional vehicle technologies to domestic Chinese firms, we find that within the emerging plug-in vehicle sector it may actually be (potentially inadvertently) protecting independent firms from tough foreign competition.

When asking Chery managers and engineers—including the founder of Chery’s New Energy Vehicle R&D department—why they began exploring plug-in vehicle research so early in its infancy, the consistent reply was to “*capture the market opportunity*” left by the international automakers that were hesitating to develop plug-in vehicles for China.³² Likewise, Haike employees noted how foreign automakers like Toyota and Ford that control the patents on the most dominant traditional electric hybrid drivetrains have not brought them to China. Their restraint may be due to IP sharing requirements within the JV system, local content requirements for subsidy eligibility, and high import tariffs (25%). This lack of entry by leaders in electric hybrid drivetrains leaves an opportunity for domestic firms to develop low cost alternative hybrid transmissions. In addition, the influx of nearly all of the world’s most experienced automakers into China through multiple JV firms during the late 1990s and early 2000s produced a wealth of foreign-trained Chinese engineers and managers, many of whom were underutilized at their respective JV firms. This large human capital resource formed the foundation of Chery’s first automotive R&D center.

In addition to creating disincentives for foreign firms to bring emerging plug-in vehicle technologies to China, prior studies on automotive technology transfer have shown how the JV institution has limited the R&D and innovation capabilities of Chinese JV parent firms [165]. Nam (2011) uses a case study approach to illustrate how Chinese JV parent firms are engaged in a “passive” learning mode with their foreign partners, leaving independent innovation capabilities undeveloped [159]. Other research has empirically shown that the JV system has even discouraged Chinese JV parent firms from investing in products that might compete with their JV partner’s products to avoid cannibalization [161]. Referring to JV parent firms’ dependence on foreign partners for technology and brands, former machinery and industry minister He Guangyuan famously said, “*It’s like opium. Once you’ve had it you will get addicted forever*” [171]. The experience of South Korean automak-

³²Interviews 15, 16, 17, 20, 22, 23, 33.

ers provides an example in a different national context in which firms also were developmentally limited by their JV relationships. Lee & Lim (2001) discuss how early joint ventures between South Korea's Hyundai and Japan's Mitsubishi restricted Hyundai's ability to learn how to develop and manufacture engines. To grow as a firm, Hyundai instead formed collaborative relationships with external suppliers such as Ricardo to co-develop engines, enabling Hyundai to not only develop its own capabilities in engine design, but also skip past older carburetor-based engines in favor of emerging electronic injection-based engines [172].

Evidence from the telecommunication equipment industry also points to inefficiencies in facilitating technology catch-up through joint ventures. In comparison with the automotive industry, He & Mu (2012) highlight that opening the telecommunication equipment market to intense competition motivated domestic firms to leverage low cost inputs and focus on different market segments to increase market share. In contrast, industrial policy aimed at consolidation in the automobile industry reduced competition, which gave monopolistic power to only a few JV firms with little motivation to develop new technologies and restricted the entry of independent domestic firms [173].

5.7.2 Local Protectionism as an Innovation Incubator

Like many other industries in China, the plug-in vehicle sector has been marked by extreme local protectionism, with local governments instituting policies that favor local players. By protecting the local market from outside competition and providing development support, these practices have provided local firms with extended incubation environments for many years. For example, during and immediately following the 2009 TCTV program, many of the cities and provinces protected their local markets from domestic competition by restricting incentives, such as subsidies, to locally produced models. Although today the central government is denouncing these practices, some cities still maintain them in more subtle forms. In Beijing (where Beijing Auto only makes a BEV), many of the incentives are restricted to BEVs and exclude PHEVs, while in Shanghai (where Shanghai Auto is strongly pushing its PHEV) incentives are available to both BEVs and PHEVs. It is no surprise that in 2014 99% of Beijing's plug-in vehicle sales were BEVs and 81% of Shanghai's plug-in vehicle sales were PHEVs.

In addition to market protection, local governments are providing development support for new energy vehicle firms. One of the reasons the founders of Haike Technologies chose to locate in

Changzhou was to benefit from the local support such as reduced pilot production plant rent and free office space. Kandi's entire history is marked with strong relationships to both the city government of Hangzhou as well as many plug-in vehicle R&D projects supported by local government organizations. These strong relationships have enabled Kandi to secure the necessary land and infrastructure required to successfully run their rental service, which heavily depends on parking and charging infrastructure. In its earliest years, Chery also benefited from strong support by the local Wuhu city government. The city not only gave Chery an early captive market by requiring taxi companies to purchase its gasoline vehicles, but also helped insulate Chery from central government investigation while illegally producing vehicles without a production license. Local governments are also helping LSEV makers like Jiayuan (perhaps inadvertently) by allowing them to exist in a regulatory gray area. With LSEV sales booming, local governments have allowed continued LSEV sales without requiring consumers to have a driver's license or a license plate, enabling rapid market adoption.

These results suggest that market protection and development support provided by local institutions may be serving as incubators for a variety of innovations in their early development stages. While the longer-term effect of this incubation is uncertain, past literature on differences between national and regional innovation systems has suggested that there may be opportunities for complementary outcomes. Breznitz & Murphree (2011) and Nahm (2014) both find that although investments made by local governments in manufacturing capabilities instead of riskier R&D capabilities were made for the direct benefit of local businesses, the longer-term outcome has resulted in new forms of innovation capabilities. Specifically, local manufacturing firms have become specialized in "the organization of production, manufacturing techniques and technologies, delivery, design, and second-generation innovation" [103]. In a similar manner, the variety of new innovations observed in China's plug-in vehicle sector may also be an unexpected result of local institutional support for local businesses.

5.7.3 Domestic Market Characteristics Matter

In addition to its unique institutional environment, China is also home to a large, heterogeneous domestic market that is rapidly evolving over time. The size and diversity of consumer needs and income levels provide firms the opportunity to experiment with new ideas and products to

meet the needs of a large variety of market segments. While independent Chinese firms like Chery are pursuing plug-in vehicles to grasp a market opportunity at the technological frontier, firms like Jiayuan are focusing on LSEVs at the low-end market segments targeting urban and rural consumers who want motorized mobility but cannot afford a traditional car. Others like Kandi are targeting urban consumers who want the conveniences of driving a car but without the cost or hassle of owning one in crowded Chinese cities. Haike is taking a different approach altogether and focusing on a low-cost hybrid transmission that could supply multiple segments of plug-in and hybrid vehicles.

The variety and size of so many different types of consumers with different needs in China may partially explain why these firms can co-exist while innovating in different ways. With a large enough population in each segment, consumer demand could be sustaining the different risks these firms are taking by entering the plug-in vehicle market in different ways, which may not be the case in smaller markets or those with more uniform market needs. Existing theory also suggests that China's large market size and variety of segments is crucial for innovation. Brandt & Thun (2016) argue that the market dynamics between low-end domestic firms and high-end foreign firms that fosters new innovation capabilities requires large segments at both ends of the market, otherwise low-end firms cannot gain scale and high-end firms lack incentives to localize activities [131]. However, whereas Brandt & Thun (2016) found regulatory restrictions that shortened incubation periods for domestic firms in conventional vehicles was detrimental for technology upgrading, we find in the case of plug-in vehicles that the combination of institutional and market forces might be enabling extended incubation periods, fostering a variety of innovations to emerge.

5.7.4 Supporting Moves Into New Markets

National licensing policy has also influenced the decisions of independent firms. Firms like Jiayuan with decades of experience designing and manufacturing BEVs but no capabilities with conventional vehicles have unable to acquire a domestic manufacturing license, restricting them to low-volume exports. Recent policy changes allowing firms that specialize in new energy vehicles to acquire a license has influenced their development strategy and finally enabled them to enter the domestic market. In interviews with Jiayuan's leadership, news that this policy was under

discussion was a central motivation to begin developing a LSEV for domestic sale.³³ Taking a different approach, Kandi also recently formed a JV with Geely (another prominent independent Chinese automaker) to jointly develop BEVs—a mutually beneficial relationship giving Kandi access to Geely’s manufacturing license while providing Geely with an otherwise non-existent new energy vehicle business.³⁴

5.7.5 Policy Implications

Our results show conflicting policy implications at the national and local levels. Tensions may be even more extreme in the context of China’s goals with respect to new energy vehicle development, namely energy security, environmental sustainability, and technological leadership. From an energy security perspective, the diversity of plug-in vehicle innovations may provide more alternatives to conventional vehicles, potentially reducing oil consumption in the automotive industry. However, given the wide use of coal for China’s electric grid, it is disputable whether environmental goals can be achieved with plug-in vehicles in the context of China, at least in the near-term future [10,15,16,174,175]. For electric vehicle development to have a positive effect on the environment in addition to energy security will require complementary regulation aimed at cleaning up the energy sources for China’s electric grid.

With respect to technological leadership within the plug-in vehicle industry, China’s institutions may have thus far been facilitating the advancement of the sector, but going forward these institutions may need to evolve to avoid hindering future achievements. While protection from foreign competition may be helpful in early development stages, researchers have argued that eventually exposing firms to global competition is important for sustaining a strong national innovation system [122,138]. Similar arguments have been made specifically in the context of technology catch-up in China [116,165]. It is thus unclear if the current protection from JV competition in plug-in vehicles provided by national institutions may harm independent Chinese firms in the longer term by preventing them from having the incentives to compete in the global marketplace.

At the regional level, it remains unclear how local protectionism will impact firms’ capabilities for later expansion and the development of China’s overall plug-in vehicle sector. Although tight

³³Interview 32.

³⁴Interviews 31 & 32.

collaborations with local governments and power suppliers have helped new business models like Kandi's car share service, expansion into other cities could be limited by local governments restricting necessary land or infrastructure in the interest of their own local players. China has also lagged behind many other nations with emerging plug-in vehicle sectors such as the U.S. and Japan in implementing national charging standards. Although a uniform national standard does exist, local implementation has followed different norms. Local governments sometimes establish their own standards between local automakers and local charging station manufacturers. As a result, plug-in vehicles designed and manufactured in city A can rarely interface with charging infrastructure in city B—another reason why automakers have struggled to increase plug-in vehicle sales outside of their home cities.³⁵ Finally, pilot cities for programs like TCTV have historically been selected by the central government based on size and regional economic significance rather than the capabilities of their automakers. Chery Auto, based in the smaller city of Wuhu in Anhui Province, did not receive support from the TCTV program; instead, support was directed to their provincial competitor Jianghuai Automobile (JAC), located in Hefei, the capital and largest city in Anhui province, despite the fact that Chery's vehicle sales were nearly 2.5 times those of JAC at the time. For these reasons, we suspect that continued, unbridled local protectionism may hinder the future growth of China's overall plug-in vehicle sector by limiting the ability of independent Chinese firms to expand to domestic regions beyond their home cities and limiting necessary national coordination efforts such as charging infrastructure build out.

5.8 Conclusions

Scholars have previously disagreed on the type of innovation occurring within firms in China. While some suggest firms predominantly conduct process innovations in mass manufacturing [116–120], others point to an emerging and more complex form of product-process co-development that often occurs further downstream in technology commercialization and redefinition [103–108].

Our findings suggest that the innovation environment in China may be richer and more diverse than these previous scholars have suggested. Specifically, we find a large heterogeneity of innovative activities alone within one industry sector (plug-in vehicles). Independent domestic Chinese firms

³⁵Interview 13.

in electric vehicles are innovating in a wide variety of directions with respect to vehicle technology and organizational and business strategies. China's unique institutions and large, heterogeneous domestic market may together be providing just the right conditions for a diverse innovation environment in the plug-in vehicle sector. National institutions such as the formal JV system as well as local content requirements provide protection from foreign competition while local institutions may be providing further market protection and development support, creating incubation periods for independent domestic firms to grow in different directions during development stages. At the same time, China's domestic market is both diverse enough in consumer needs and large enough in size to sustain such a variety of innovations within the same industry sector.

Since institutional protection in China's plug-in vehicle sector has co-evolved along with its large, heterogeneous market, it is difficult to consider how these forces individually might affect innovation. A market with more uniform needs might lead to more uniform innovation directions whereas a more diverse market might lead to more diverse innovation directions. In addition, the market size in each situation could impact the economic feasibility of innovations, with smaller sizes limiting the variety of feasible innovations. Stronger versus weaker institutional protections for domestic firms may lead to differences in whether market needs are met by indigenous versus foreign firms but also the length of incubation time firms have to develop innovations. Examining these dimensions may help policy makers and business leaders in other developing nations that have large, emerging markets, such as the "BRIC" (Brazil, Russia, India, and China) and "MINT" (Mexico, Indonesia, Nigeria and Turkey) nations [176]. As juxtaposition, even though developed nations such as the United States also have large domestic markets, the personal mobility needs and available transportation infrastructure are far more homogeneous compared to those in China. Gasoline infrastructure is readily available in urban and rural environments, consumers have fewer intercity transit alternatives, and higher incomes enable the vast majority of the population to own a conventional personal vehicle. Thus even though its market size is large, we would still expect to observe a more uniform innovation direction in the emerging plug-in vehicle sector in the U.S. (in this case, "up").

Future work should explore the extent to which our findings extend to other sectors. Whereas existing literature on technology catch-up focuses on how firms in developing nations learn and acquire *existing* know-how and technologies [116, 165, 177, 178], plug-in vehicles are relatively new

to the world. Unlike with conventional vehicles, established global automotive firms have not had decades to master plug-in vehicle design, production, and marketing, and these firms all largely face similar technological challenges in terms of improving battery and motor performance while reducing cost. Thus given the newness of this sector, there may be less existing technology and know-how for domestic firms to acquire.

While national and local institutions may have allowed independent Chinese firms to capture the majority of the emerging plug-in vehicle market, continuing in this direction could undermine extended domestic and even international growth. The lack of functional national charging standards could inhibit the ability of firms to expand to other domestic markets, and the lack of foreign competition could inhibit their expansion into international markets. Depending on national and local goals, policy makers should reconsider policies that might restrict market entry, such as the joint venture ownership system and automobile manufacturing licensing restrictions.

Chapter 6

Conclusions

6.1 Summary of Contributions and Policy Implications

This thesis assesses how consumer preferences, national and local institutions, market characteristics, and policy are associated with the development and adoption of plug-in vehicles in China. The contributions of each study have important policy implications.

In Chapter 3, conjoint surveys I fielded in the U.S. and China revealed that while Chinese consumers may be more willing to accept today's full-electric BEVs, American consumers have stronger preferences towards lower-range PHEVs. Nonetheless, with the combined bundle of attributes offered by vehicles available today, mainstream consumers in both countries prefer gasoline models over their plug-in counterparts. The study was also the first to field identical conjoint surveys on consumer preferences for plug-in vehicles between the U.S. and China, enabling the direct comparison of results. The implied potential for earlier BEV adoption in China (given adequate supply) leaves policy makers in China with important decisions about continuing support for plug-in vehicles. While past studies have concluded that in some regions BEVs may actually increase local emissions in China, the effect on global emissions is unclear. Given the size of China's market, rapid growth in plug-in vehicle adoption in China may change the global incentives to invest and develop plug-in vehicle technologies worldwide.

A known limitation of Chapter 3 is that it is based on survey data, which may or may not reflect consumer behavior in the real market. One approach to potentially mitigating this limitation is to pool together survey and market sales data in a joint model. In Chapter 4, I use a synthetic data

experiment to explore the benefits of the pooling approach when there are endogenous parameters in the market data (a commonly cited source of parameter bias in market choice data) and when consumer response to attributes is different in the survey context versus the market for which we want to recover parameters. Results suggest that the presence of these factors can greatly affect pooled model parameter estimates. This finding is in contrast to past literature that has largely presented pooling as a method to “mitigate the weaknesses” of market and survey data. I also show that when endogeneity is present in the market data, the likelihood ratio test that is frequently used to justify pooling is neither necessary nor sufficient to determine whether survey and market data should be pooled. I provide new guidelines for understanding under what conditions pooling data sources may or may not be advisable for accurately estimating true market preference parameters, including consideration of the context and conditions under which the data were generated as well as the relative balance of information between data sources. This understanding of the sensitivities of pooled models to characteristics of data sets can have important implications for policy decisions based on accurate model outcomes.

In Chapter 5, I examined vehicle sales data, archival data, and the results of 37 in-depth interviews with automotive managers and engineers. Case studies on four domestic firms in China’s plug-in vehicle sector revealed a diversity of innovative activity and three distinct directions of innovation (“up,” “down,” and “sideways”) with respect to vehicle technology and organizational and business strategies. The results illustrate a richer and more diverse innovation environment in China than previous scholars have suggested. In addition, the study builds new theory about how the co-evolution of national institutions, local institutions, and market characteristics can shape innovation directions. I theorize that while national institutions such as the joint venture system may be inadvertently discouraging international joint venture firms from entering China’s plug-in vehicle sector, regional institutions such as local protectionism may be serving as incubators for a variety of innovations within independent domestic firms in their early development stages; these institutional protections along with demand from China’s large, heterogeneous domestic market may help explain the presence of the observed variety of innovations. As these domestic firms begin to grow beyond their protected regional markets, national institutions may need to evolve to support national standardization of policies and plug-in infrastructure. Depending on national and local goals, policy makers should reconsider policies that might restrict market entry, such as

the joint venture ownership system and automobile manufacturing licensing restrictions.

6.2 Open Questions

The studies within this thesis raised several questions that remain unanswered. Chapter 3 concludes that Chinese consumers may be more willing to accept BEVs than American consumers, but the study was based on survey results from four major Chinese cities in 2012 when virtually no plug-in vehicles were on the market. Given that today multiple plug-in vehicle technologies are being sold in China, will preferences change as Chinese consumers gain more experience with these technologies? How do preferences differ between consumers in large Tier 1 cities like those in my survey and consumers in Tier 2 and Tier 3 cities that have less vehicle restrictions, and how does reliable access to charging infrastructure affect consumer choices? Answers to such questions are needed to adapt policies to a potentially changing market environment.

In addition, while Chapter 4 illustrates how endogeneity and context effects can result in biased coefficient estimates in a pooled model, a method for resolving these issues in a pooled framework remains unexplored. An interesting direction forward would be to develop methods for using the pooled structure to correct for an endogenous parameter. For example, if an endogenous parameter in one data set is believed to be exogenous in another, would it be possible to use the information from the latter data set to identify the endogenous parameter in the former data set through a pooled model framework?

Finally, Chapter 5 illustrates a diversity of innovative activity within China's plug-in vehicle sector, but it is unclear whether any of these observations are generalizable to other nations or industries. Future research is needed to investigate what characteristics of the plug-in vehicle sector are related to this diversity of innovation directions as well as which aspects of China's institutional and market characteristics (if any) may be generalized to other nations.

6.3 Elevator Speeches

The "elevator speech" is a clear, brief, and informed message about a topic. The name comes from a hypothetical situation in which one has just a single, quick elevator ride during which to share an idea with another person. In EPP, the frequently posed scenario involves an elevator ride with an

important policy decision maker. For this thesis, I decided to write down some elevator speeches that succinctly summarize some major findings from this thesis:

- To a Chinese government official: *Demand in China's plug-in vehicle sector is being primarily met by domestic Chinese firms supported by their local governments, but in order to expand beyond their local markets, these firms may ultimately need 1) to be exposed to global competition and 2) stronger coordination efforts at the national level to overcome some of the negative consequences of too much local protection, such as the lack of a functional national charging standards.*
- To a U.S. government official: *Demand for plug-in vehicles in China may soon surpass that in the U.S. To encourage our national firms to compete in that market, we should encourage the Chinese government to pursue relaxation of restrictive policies such as the joint venture institution and local content requirements on plug-in vehicle components. Such measures could also be potentially beneficial for Chinese firms in the plug-in vehicle sector by exposing them to global competition and encouraging growth beyond local markets.*
- To a joint China-U.S. government committee: *Plug-in vehicle development in China is being met at the local level, yet national coordination on supporting infrastructure, such as charging standards, remains less developed. Establishing international standards for both nations could be mutually beneficial for future expansion of the global plug-in vehicle sector.*
- To an automotive business leader interested in entering China's plug-in sector: *Responding to growing Chinese demand for plug-in vehicles will require an intimate understanding of the market needs in order to inform an appropriate innovation strategy. In the Chinese context, this strategy may not necessarily be to develop advanced technology; using existing technologies and innovative business models and organizational strategies are other alternatives that some domestic Chinese businesses are already applying.*

Appendix A

Supplemental Information for Chapter 3

The supplementary information associated with this chapter can also be found on the of Helveston et al. (2015) at <http://dx.doi.org/10.1016/j.tra.2015.01.002>.

A.1 Supplemental Model Estimates

Table A1: Regression Coefficient for Un-weighted U.S. and China Models in the WTP Space

Attribute	Coef.	Model 1: MNL		Model 2: MXL	
		U.S.	China	U.S.	China
Price	μ	0.074 (0.002)***	0.035 (0.002)***	0.083 (0.003)***	0.038 (0.002)***
HEV	μ	0.807 (0.997)	5.977 (1.834)***	0.906 (1.087)	5.915 (1.883)***
	σ	--	--	1.819 (3.983)	10.244 (7.588)
PHEV10	μ	1.166 (1.066)	-0.093 (1.948)	1.289 (1.130)	0.230 (1.952)
	σ	--	--	1.587 (3.544)	2.824 (8.072)
PHEV20	μ	1.648 (1.078)	-1.653 (1.947)	2.015 (1.111)	-1.569 (1.950)
	σ	--	--	6.696 (3.186)	3.695 (7.277)
PHEV40	μ	2.580 (1.071)	2.160 (1.936)	2.476 (1.123)	2.079 (1.928)
	σ	--	--	1.090 (3.090)	1.262 (7.494)
BEV75	μ	-16.047 (1.215)***	-6.800 (2.009)***	-15.406 (1.292)***	-7.887 (2.166)***
	σ	--	--	8.979 (4.698)	17.875 (7.289)
BEV100	μ	-13.004 (1.197)***	-8.614 (2.027)***	-12.064 (1.262)***	-8.593 (2.104)***
	σ	--	--	7.879 (4.939)	8.736 (8.556)
BEV150	μ	-9.574 (1.151)***	-2.138 (1.958)	-8.433 (1.221)***	-2.055 (1.963)
	σ	--	--	6.742 (4.564)	0.457 (8.351)
American	μ	2.344 (0.796)***	-7.788 (1.458)***	2.624 (0.840)***	-6.864 (1.569)***
	σ	--	--	3.448 (2.802)	11.360 (6.259)
Japanese	μ	-0.375 (0.792)	-13.371 (1.536)***	-0.068 (0.816)	-12.628 (1.637)***
	σ	--	--	7.462 (3.388)	10.057 (5.992)
Chinese	μ	-10.269 (0.870)***	-6.518 (1.418)***	-10.180 (0.902)***	-5.864 (1.563)***
	σ	--	--	1.393 (0.301)***	27.724 (7.391)***
S. Korean	μ	-6.031 (0.833)***	-13.353 (1.534)***	-5.654 (0.872)***	-13.659 (1.892)***
	σ	--	--	0.352 (0.549)	34.504 (7.856)***
PHEV Fast-charge	μ	2.879 (0.812)***	7.472 (1.482)***	3.175 (0.838)***	7.726 (1.495)***
	σ	--	--	3.447 (3.031)	3.319 (5.968)
BEV Fast-charge	μ	2.919 (0.907)***	5.662 (1.517)***	2.632 (1.006)***	5.792 (1.539)***
	σ	--	--	5.513 (2.709)	1.480 (6.444)
Operating Cost	μ	-1.636 (0.067)***	-2.942 (0.225)***	-1.758 (0.101)***	-3.009 (0.242)***
	σ	--	--	1.477 (3.265)	2.770 (1.084)
Acceleration Time	μ	-1.697 (0.159)***	-4.915 (0.296)***	-1.709 (0.163)***	-4.964 (0.300)***
	σ	--	--	5.637 (3.705)	1.492 (0.877)
LL at Convergence:		-4617.0	-6655.6	-4588.0	-6632.5
Null LL:		-6328.0	-7382.7	-6328.0	-7382.7
AIC:		9265.9	13343.1	9237.9	13327.1
McFadden R ² :		0.27	0.10	0.27	0.10
Adj. McFadden R ² :		0.27	0.10	0.27	0.10
Num. of Obs:		5760	6720	5760	6720

Table A2: Regression Coefficient for Weighted U.S. and China Models in the Preference Space

Attribute	Coef.	Model 1: MNL		Model 2: MXL	
		U.S.	China	U.S.	China
Price	μ	-0.052 (0.002)***	-0.033 (0.002)***	0.066 (0.003)***	-0.039 (0.002)***
HEV	μ	-0.061 (0.084)	0.163 (0.063)***	-0.418 (1.585)	0.185 (0.077)
	σ	--	--	0.188 (4.664)	0.762 (0.303)
PHEV10	μ	0.001 (0.093)	-0.042 (0.069)	0.822 (1.796)	-0.070 (0.081)
	σ	--	--	2.197 (5.428)	0.247 (0.341)
PHEV20	μ	0.088 (0.091)	-0.040 (0.068)	3.207 (1.734)	-0.090 (0.080)
	σ	--	--	8.664 (5.719)	0.161 (0.265)
PHEV40	μ	0.138 (0.093)	0.032 (0.067)	3.304 (1.741)	0.011 (0.079)
	σ	--	--	7.141 (5.466)	0.360 (0.243)
BEV75	μ	-1.053 (0.100)***	-0.200 (0.069)***	-18.453 (1.934)***	-0.310 (0.092)***
	σ	--	--	4.175 (6.232)	1.174 (0.289)***
BEV100	μ	-1.019 (0.100)***	-0.270 (0.070)***	-18.947 (1.965)***	-0.400 (0.086)***
	σ	--	--	1.898 (5.368)	-0.331 (0.290)
BEV150	μ	-0.716 (0.100)***	0.044 (0.068)	-12.727 (1.959)***	0.021 (0.080)
	σ	--	--	10.486 (6.061)	0.276 (0.253)
American	μ	0.428 (0.066)***	-0.352 (0.049)***	7.432 (1.268)***	-0.306 (0.063)***
	σ	--	--	0.665 (3.439)	0.745 (0.234)***
Japanese	μ	0.049 (0.067)	-0.602 (0.050)***	-0.577 (1.289)	-0.602 (0.063)***
	σ	--	--	11.765 (3.508)***	0.919 (0.236)***
Chinese	μ	-0.993 (0.074)***	-0.322 (0.048)***	-19.848 (1.666)***	-0.251 (0.064)***
	σ	--	--	8.078 (4.173)	1.349 (0.260)***
S. Korean	μ	-0.497 (0.071)***	-0.644 (0.050)***	-10.412 (1.378)***	-0.718 (0.078)***
	σ	--	--	12.335 (3.850)***	2.148 (0.241)***
PHEV Fast-charge	μ	0.206 (0.069)***	0.253 (0.051)***	3.331 (1.335)	0.304 (0.063)***
	σ	--	--	8.882 (4.396)	-0.788 (0.210)***
BEV Fast-charge	μ	0.175 (0.077)	0.221 (0.052)***	0.030 (1.821)	0.255 (0.064)***
	σ	--	--	26.237 (3.871)***	-0.457 (0.208)
Operating Cost	μ	-0.083 (0.005)***	-0.107 (0.006)***	-1.626 (0.104)***	-0.134 (0.008)***
	σ	--	--	0.076 (0.247)	-0.128 (0.037)***
Acceleration Time	μ	-0.061 (0.013)***	-0.155 (0.007)***	-1.269 (0.293)***	-0.189 (0.010)***
	σ	--	--	5.766 (0.880)***	-0.133 (0.037)***
LL at Convergence:		-3425.6	-6788.8	-3373.1	-6721.0
Null LL:		-4360.6	-7487.3	-4360.6	-7487.3
AIC:		6883.3	13609.6	6808.3	13503.9
McFadden R ² :		0.21	0.09	0.23	0.10
Adj. McFadden R ² :		0.21	0.09	0.22	0.10
Num. of Obs:		5760	6720	5760	6720

Signif. codes: '***' <= 0.001, '**' <= 0.01, '*' <= 0.05. Standard errors of estimates are presented in parenthesis.

Table A3: Regression Coefficient for Un-weighted U.S. and China Models in the Preference Space

Attribute	Coef.	Model 1: MNL		Model 2: MXL	
		U.S.	China	U.S.	China
Price	μ	-0.074 (0.002)***	-0.035 (0.002)***	-0.083 (0.003)***	-0.038 (0.002)***
HEV	μ	0.059 (0.074)	0.209 (0.064)***	0.076 (0.085)	0.241 (0.071)***
	σ	--	--	-0.090 (0.342)	0.391 (0.296)
PHEV10	μ	0.086 (0.079)	-0.003 (0.068)	0.109 (0.089)	0.004 (0.076)
	σ	--	--	-0.078 (0.343)	-0.115 (0.312)
PHEV20	μ	0.122 (0.080)	-0.058 (0.068)	0.140 (0.089)	-0.065 (0.076)
	σ	--	--	-0.544 (0.282)	-0.145 (0.282)
PHEV40	μ	0.190 (0.079)	0.076 (0.068)	0.224 (0.088)	0.082 (0.075)
	σ	--	--	-0.186 (0.293)	0.053 (0.290)
BEV75	μ	-1.186 (0.087)***	-0.238 (0.070)***	-1.439 (0.150)***	-0.276 (0.081)***
	σ	--	--	-1.576 (0.420)***	0.711 (0.282)
BEV100	μ	-0.961 (0.087)***	-0.302 (0.070)***	-1.186 (0.149)***	-0.339 (0.082)***
	σ	--	--	-1.725 (0.382)***	-0.322 (0.329)
BEV150	μ	-0.707 (0.084)***	-0.075 (0.068)	-0.771 (0.113)***	-0.078 (0.077)
	σ	--	--	-1.075 (0.355)***	-0.010 (0.321)
American	μ	0.173 (0.059)***	-0.273 (0.050)***	0.183 (0.067)***	-0.246 (0.061)***
	σ	--	--	-0.319 (0.222)	0.441 (0.240)
Japanese	μ	-0.028 (0.059)	-0.468 (0.050)***	-0.035 (0.066)	-0.469 (0.062)***
	σ	--	--	-0.380 (0.226)	0.391 (0.231)
Chinese	μ	-0.759 (0.062)***	-0.228 (0.049)***	-0.840 (0.071)***	-0.185 (0.059)***
	σ	--	--	0.265 (0.244)	1.092 (0.285)***
S. Korean	μ	-0.446 (0.061)***	-0.468 (0.050)***	-0.527 (0.072)***	-0.473 (0.067)***
	σ	--	--	-0.542 (0.241)	1.352 (0.301)***
PHEV Fast-charge	μ	0.213 (0.060)***	0.261 (0.051)***	0.243 (0.066)***	0.290 (0.057)***
	σ	--	--	-0.228 (0.247)	-0.135 (0.230)
BEV Fast-charge	μ	0.216 (0.067)***	0.198 (0.052)***	0.223 (0.098)	0.219 (0.058)***
	σ	--	--	-0.090 (0.288)	-0.067 (0.247)
Operating Cost	μ	-0.121 (0.004)***	-0.104 (0.007)***	-0.134 (0.005)***	-0.119 (0.008)***
	σ	--	--	0.049 (0.024)	-0.105 (0.041)
Acceleration Time	μ	-0.125 (0.012)***	-0.172 (0.007)***	-0.139 (0.013)***	-0.192 (0.009)***
	σ	--	--	0.017 (0.049)	-0.058 (0.034)
LL at Convergence:		-4617.0	-6655.6	-4588.7	-6632.5
Null LL:		-6328.0	-7382.7	-6328.0	-7382.7
AIC:		9265.9	13343.1	9239.3	13327.0
McFadden R ² :		0.27	0.10	0.27	0.10
Adj. McFadden R ² :		0.27	0.10	0.27	0.10
Num. of Obs:		5760	6720	5760	6720

Signif. codes: '***' <= 0.001, '**' <= 0.01, '*' <= 0.05. Standard errors of estimates are presented in parenthesis.

Table A4: Regression Coefficients for Models Interacting Respondent Demographics with Vehicle Attributes in the U.S. in the Preference Space

Attribute	Model 3: Base case	Model 4: Income	Model 5: Age	Model 6: Other Demographics
Price	-0.052 (0.002)***	-0.098 (0.005)***	-0.083 (0.007)***	-0.067 (0.007)***
HEV	-0.061 (0.084)	0.996 (0.174)***	0.109 (0.235)	0.621 (0.268)
PHEV10	0.001 (0.093)	0.821 (0.182)***	0.187 (0.235)	0.972 (0.284)***
PHEV20	0.089 (0.091)	0.632 (0.169)***	0.239 (0.237)	0.788 (0.283)***
PHEV40	0.139 (0.093)	0.803 (0.179)***	0.353 (0.234)	0.717 (0.286)
BEV75	-1.053 (0.100)***	-0.130 (0.185)	-1.100 (0.255)***	0.013 (0.302)
BEV100	-1.019 (0.100)***	-0.572 (0.182)***	-0.937 (0.252)***	-0.428 (0.312)
BEV150	-0.716 (0.100)***	-0.226 (0.194)	-0.685 (0.246)***	-0.691 (0.298)
PHEV Fast-charge	0.206 (0.069)***	0.201 (0.070)***	0.210 (0.069)***	0.229 (0.071)***
BEV Fast-charge	0.175 (0.077)	0.181 (0.078)	0.184 (0.078)	0.197 (0.079)
Operating Cost	-0.084 (0.005)***	-0.127 (0.010)***	-0.157 (0.015)***	-0.145 (0.016)***
Acceleration Time	-0.061 (0.013)***	-0.066 (0.013)***	-0.062 (0.013)***	-0.063 (0.014)***
American	0.428 (0.066)***	0.442 (0.067)***	0.434 (0.067)***	0.466 (0.068)***
Japanese	0.049 (0.067)	0.043 (0.069)	0.048 (0.068)	0.072 (0.069)
Chinese	-0.994 (0.074)***	-1.029 (0.075)***	-1.000 (0.074)***	-0.992 (0.075)***
S. Korean	-0.497 (0.071)***	-0.505 (0.072)***	-0.500 (0.071)***	-0.501 (0.072)***
High Income * Price	--	0.058 (0.006)***	--	--
High Income * Op. Cost	--	0.057 (0.011)***	--	--
High Income * HEV	--	-1.380 (0.201)***	--	--
High Income * PHEV10	--	-1.041 (0.203)***	--	--
High Income * PHEV20	--	-0.703 (0.193)***	--	--
High Income * PHEV40	--	-0.856 (0.202)***	--	--
High Income * BEV75	--	-1.230 (0.212)***	--	--
High Income * BEV100	--	-0.611 (0.207)***	--	--
High Income * BEV150	--	-0.660 (0.217)***	--	--
High Age * Price	--	--	0.035 (0.007)***	--
High Age * Op. Cost	--	--	0.084 (0.016)***	--
Has Child * Op. Cost	--	--	--	0.047 (0.012)***
Has Child * HEV	--	--	--	-0.945 (0.211)***
Female * PHEV20	--	--	--	-0.799 (0.191)***
Married * BEV75	--	--	--	-0.705 (0.239)***
Household Size * BEV75	--	--	--	-0.342 (0.099)***
Household Size * BEV100	--	--	--	-0.335 (0.092)***
College Grad * Price	--	--	--	0.026 (0.005)***
College Grad * Op. Cost	--	--	--	0.049 (0.012)***
College Grad * BEV150	--	--	--	0.806 (0.227)***
LL at Convergence:	-3425.6	-3327.0	-3399.1	-3313.5
Null LL:	4360.6	4360.6	4360.6	4360.6
AIC:	-6883.3	-6703.9	-6848.3	-6749.0

McFadden R ² :	0.21	0.24	0.22	0.24
Adj. McFadden R ² :	0.21	0.23	0.22	0.23
Num. of Observations:	5760	5760	5760	5760

Signif. codes: '***' <= 0.001, '**' <= 0.01, '*' <= 0.05. Standard errors of estimates are presented in parenthesis.

Table A5: Regression Coefficients for Models Interacting Respondent Experience and Attitude with Vehicle Attributes in the U.S. in the Preference Space

Attribute	Model 3: Base case	Model 7: Driving Experience	Model 8: Attitude
Price	-0.052 (0.002)***	-0.078 (0.007)***	-0.062 (0.003)***
HEV	-0.061 (0.084)	0.321 (0.262)	-0.303 (0.113)***
PHEV10	0.001 (0.093)	0.821 (0.328)	-0.255 (0.119)
PHEV20	0.089 (0.091)	0.055 (0.340)	-0.251 (0.118)
PHEV40	0.139 (0.093)	0.173 (0.331)	-0.083 (0.118)
BEV75	-1.053 (0.100)***	-0.936 (0.356)***	-1.502 (0.130)***
BEV100	-1.019 (0.100)***	-0.277 (0.368)	-1.570 (0.134)***
BEV150	-0.716 (0.100)***	-1.321 (0.354)***	-1.037 (0.132)***
PHEV Fast-charge	0.206 (0.069)***	0.198 (0.070)***	0.202 (0.070)***
BEV Fast-charge	0.175 (0.077)	0.207 (0.078)***	0.194 (0.078)
Operating Cost	-0.084 (0.005)***	-0.138 (0.015)***	-0.087 (0.006)***
Acceleration Time	-0.061 (0.013)***	-0.060 (0.013)***	-0.065 (0.013)***
American	0.428 (0.066)***	0.427 (0.067)***	0.448 (0.067)***
Japanese	0.049 (0.067)	0.056 (0.068)	0.072 (0.068)
Chinese	-0.994 (0.074)***	-0.997 (0.074)***	-1.005 (0.074)***
S. Korean	-0.497 (0.071)***	-0.512 (0.072)***	-0.477 (0.072)***
Num. Vehicles * Price	--	0.012 (0.003)***	--
Num. Vehicles * Op. Cost	--	0.027 (0.007)***	--
Env. Appear. * HEV	--	--	0.570 (0.195)***
Env. Appear. * PHEV40	--	--	0.534 (0.201)***
Env. Appear. * BEV100	--	--	1.230 (0.205)***
Stat. Symbol * Price	--	--	0.018 (0.004)***
Stat. Symbol * PHEV20	--	--	0.772 (0.183)***
Stat. Symbol * BEV75	--	--	0.846 (0.194)***
Stat. Symbol * BEV100	--	--	0.538 (0.201)***
Stat. Symbol * BEV150	--	--	0.623 (0.193)***
LL at Convergence:	-3425.6	-3383.9	-3379.8
Null LL:	4360.6	4360.6	4360.6
AIC:	-6883.3	-6847.7	-6825.6
McFadden R ² :	0.21	0.22	0.23
Adj. McFadden R ² :	0.21	0.22	0.22
Num. of Observations:	5760	5760	5760

Signif. codes: '***' <= 0.001, '**' <= 0.01, '*' <= 0.05. Standard errors of estimates are presented in parenthesis.

Table A6: Regression Coefficients for Models Interacting Respondent Demographics with Vehicle Attributes in China in the Preference Space

Attribute	Model 3: Base case	Model 4: Income	Model 5: Age	Model 6: Other Demographics
Price	-0.033 (0.002)***	-0.029 (0.002)***	-0.033 (0.003)***	-0.042 (0.006)***
HEV	0.163 (0.063)	0.103 (0.093)	0.044 (0.121)	0.144 (0.221)
PHEV10	-0.043 (0.069)	0.035 (0.097)	0.000 (0.119)	-0.158 (0.225)
PHEV20	-0.041 (0.068)	-0.131 (0.096)	-0.035 (0.118)	-0.547 (0.220)
PHEV40	0.031 (0.067)	-0.028 (0.098)	-0.038 (0.117)	-0.252 (0.215)
BEV75	-0.200 (0.069)***	-0.278 (0.098)***	-0.308 (0.120)	-0.411 (0.218)
BEV100	-0.271 (0.070)***	-0.217 (0.100)	-0.306 (0.121)	-0.742 (0.234)***
BEV150	0.044 (0.068)	-0.092 (0.097)	0.072 (0.117)	-0.233 (0.219)
PHEV Fast-charge	0.253 (0.051)***	0.257 (0.051)***	0.254 (0.051)***	0.258 (0.051)***
BEV Fast-charge	0.221 (0.052)***	0.218 (0.052)***	0.220 (0.052)***	0.221 (0.053)***
Operating Cost	-0.107 (0.006)***	-0.084 (0.010)***	-0.099 (0.012)***	-0.148 (0.023)***
Acceleration Time	-0.155 (0.007)***	-0.155 (0.007)***	-0.155 (0.007)***	-0.157 (0.007)***
American	-0.352 (0.049)***	-0.350 (0.049)***	-0.353 (0.049)***	-0.359 (0.050)***
Japanese	-0.602 (0.050)***	-0.606 (0.050)***	-0.603 (0.050)***	-0.613 (0.050)***
Chinese	-0.322 (0.048)***	-0.319 (0.048)***	-0.323 (0.048)***	-0.322 (0.049)***
S. Korean	-0.644 (0.050)***	-0.651 (0.050)***	-0.648 (0.050)***	-0.652 (0.051)***
High Income * Op. Cost	--	-0.041 (0.013)***	--	--
Household Size * Price	--	--	--	0.004 (0.001)***
Household Size * Op. Cost	--	--	--	0.018 (0.006)***
Household Size * PHEV40	--	--	--	0.142 (0.054)***
College Grad * Price	--	--	--	-0.010 (0.004)***
College Grad * Op. Cost	--	--	--	-0.074 (0.015)***
Married * PHEV20	--	--	--	1.061 (0.288)***
Married * BEV100	--	--	--	0.838 (0.317)***
Married * BEV150	--	--	--	1.360 (0.324)***
Has Child * PHEV20	--	--	--	-1.007 (0.274)***
Has Child *BEV150	--	--	--	-1.351 (0.310)***
LL at Convergence:	-6788.8	-6773.6	-6785.9	-6712.3
Null LL:	7487.3	7487.3	7487.3	7487.3
AIC:	-13609.6	-13597.2	-13621.8	-13546.6
McFadden R ² :	0.09	0.10	0.09	0.10
Adj. McFadden R ² :	0.09	0.09	0.09	0.10
Num. of Observations:	6720	6720	6720	6720

Signif. codes: '***' <= 0.001, '**' <= 0.01, '*' <= 0.05. Standard errors of estimates are presented in parenthesis.

Table A7: Regression Coefficients for Models Interacting Respondent Experience and Attitude with Vehicle Attributes in China in the Preference Space

Attribute	Model 3: Base case	Model 7: Driving Experience	Model 8: Attitude
Price	-0.033 (0.002)***	-0.026 (0.006)***	-0.019 (0.003)***
HEV	0.163 (0.063)	0.010 (0.263)	-0.266 (0.134)
PHEV10	-0.043 (0.069)	0.274 (0.274)	-0.189 (0.133)
PHEV20	-0.041 (0.068)	-0.129 (0.261)	-0.056 (0.131)
PHEV40	0.031 (0.067)	0.169 (0.281)	0.190 (0.127)
BEV75	-0.200 (0.069)***	-0.333 (0.272)	-0.330 (0.129)
BEV100	-0.271 (0.070)***	-1.060 (0.275)***	-0.545 (0.137)***
BEV150	0.044 (0.068)	0.126 (0.263)	-0.040 (0.130)
PHEV Fast-charge	0.253 (0.051)***	0.242 (0.051)***	0.262 (0.051)***
BEV Fast-charge	0.221 (0.052)***	0.236 (0.053)***	0.240 (0.052)***
Operating Cost	-0.107 (0.006)***	-0.146 (0.025)***	-0.160 (0.012)***
Acceleration Time	-0.155 (0.007)***	-0.156 (0.007)***	-0.154 (0.007)***
American	-0.352 (0.049)***	-0.348 (0.049)***	-0.349 (0.049)***
Japanese	-0.602 (0.050)***	-0.599 (0.050)***	-0.608 (0.050)***
Chinese	-0.322 (0.048)***	-0.319 (0.049)***	-0.323 (0.049)***
S. Korean	-0.644 (0.050)***	-0.646 (0.050)***	-0.638 (0.050)***
Home Charge * PHEV40	--	0.578 (0.110)***	--
Home Charge * BEV100	--	0.338 (0.113)***	--
Num. Vehicles * BEV100	--	0.741 (0.207)***	--
Env. Appear. * Price	--	--	-0.011 (0.003)***
Env. Appear. * Op. Cost	--	--	0.075 (0.014)***
Env. Appear. * HEV	--	--	0.605 (0.139)***
Env. Appear. * PHEV10	--	--	0.454 (0.138)***
Env. Appear. * BEV100	--	--	0.385 (0.139)***
Env. Appear. * BEV150	--	--	0.411 (0.136)***
Stat. Symbol * Price	--	--	-0.011 (0.003)***
Stat. Symbol * BEV150	--	--	-0.343 (0.129)***
Stat. Symbol * PHEV20	--	--	-0.355 (0.127)***
Stat. Symbol * PHEV40	--	--	-0.434 (0.128)***
LL at Convergence:	-6788.8	-6728.6	-6734.8
Null LL:	7487.3	7487.3	7487.3
AIC:	-13609.6	-13537.2	-13535.7
McFadden R ² :	0.09	0.10	0.10
Adj. McFadden R ² :	0.09	0.10	0.10
Num. of Observations:	6720	6720	6720

Signif. codes: '***' <=0.001, '**' <= 0.01, '*'<= 0.05. Standard errors of estimates are presented in parenthesis.

A.2 Details on Modeling Method

Conjoint Analysis

Conjoint analysis has been widely used by marketing researchers since the 1970s to examine the relative importance of a product's many attributes to one another. The approach involves asking participants in an experiment to make trade-offs among several products, each with different levels of the same attributes. These trade-offs are typically presented in one of three ways: ranking-based, rating-based, and choice-based. In a ranking-based experiment, participants are asked to rank each alternative relative to one another; in a rating-based experiment, they are asked to give a rating along a scale of each alternative relative to one another; and in a choice-based experiment, they are simply asked to choose a single alternative that they are most likely to buy in a real buying situation. We chose the choice-based approach for this research as it more realistically mimics a true buying scenario (in which you only choose one product rather than rank several), and because it has been shown that this is especially true when price is one of the attributes shown to respondents (Huber, Wittink, & Johnson, 1992).

Discrete Choice Modeling and Maximum Likelihood Estimation

Choice-based conjoint experiments produce individual level choice data. Discrete choice models are used to relate these choices to the attributes of the alternatives shown or those of the individual respondent. These models utilize a random utility framework and some functional form relating choice probability to product and/or consumer attributes. We employ variants of the logit model (one of the most widely adopted choice models), which assume that the unobservable utility ε_{ijt} has an independent and identically distributed extreme value distribution, yielding a closed-form expression for choice probabilities as shown in equation 3.2. The explicit model used for this study as shown in equation 3.3 is the primary functional form describing the utility to a survey respondent from making a particular choice.

To estimate the model parameters in equation 3.3 we use maximum likelihood estimation. For MNL models we minimize the negative of the log-likelihood function:

$$LL(\theta) = \sum_{i=1}^I \sum_{j=1}^J d_{ij} \ln P_{ij} \quad (A1)$$

θ are the estimated parameters, P_{ij} are the choice probabilities shown in equation 3.2, and $d_{ij} = 1$ if i chose j and zero otherwise. For MXL models we used simulated maximum likelihood estimation where the simulated log-likelihood is the same as equation A1 except the choice probabilities are given by

$$\hat{P}_{ij} = \frac{1}{R} \sum_{r=1}^R P_{ij}^r \quad (\text{A2})$$

where P_{ij}^r are the choice probabilities from equation 3.2 calculated using the r^{th} draw of the parameters from their assumed distributions. The choice probabilities used in the simulated log-likelihood function are the average over all draws. This procedure is explained in detail in Train (2009). The program used to estimate all models was written by John Paul Helveston in the “R” computing language and can be downloaded from his website at www.jhelvy.com/logitr. The program package download includes further extensive documentation on the estimation procedure.

Randomized Multistart Estimation Procedure

Since the WTP space model has a non-linear in parameters utility function, the log-likelihood function could have multiple local maxima, and a global maximum is not guaranteed. To search for a global maximum, we implement a multistart algorithm that runs the same optimization algorithm multiple times using different starting points. For each model we estimate, we search using an all zero starting point as well as multiple random starting points for each parameter. For MXL models, we also run a case where we use the MNL results as starting points for the mean parameters with variances of 1. The steps of the multistart algorithm are as follows:

1. Generate a starting value for each parameter by drawing from a uniform distribution between the bounds -1 and 1 (the data was scaled to be on the order of 1 such that the bounds of -1 to 1 provide a wide search space).
2. Minimize the negative of the log-likelihood function using an optimization loop.
3. Compare the negative log-likelihood value at the solution to the current lowest negative log-likelihood value observed thus far.
4. If the new negative log-likelihood value is lower than the previous lowest, set the new lowest value to the new one and save the parameters at this new solution.

5. Repeat steps 1 - 4 many times.

We ran 20 iterations of the multistart algorithm for each different model. In each case we only found on the order of <5 local maxima, with the majority of runs converging to the same (best) local maximum. Thus we have confidence that the best local maxima found is likely the global maximum.

Sample Weighting

We compared the distributions of age and income in the sample we collected in China and the U.S. to those from a much larger, nation-wide survey provided by Ford Motor Company in each country targeting vehicle owners. Taking the un-weighted distributions from the reference survey as representative of the vehicle-buying population in each country, we found we oversampled younger, less wealthy individuals in each country with particularly strong oversampling in the U.S. (as was expected from fielding the survey online in the U.S.). To account for these differences, we weight the respondents using least squares optimization to match the age and income CDFs from our survey to those from the Maritz survey as closely as possible subject to lower and upper constraints on the weight values from 0.2 to 5 to prevent any one respondent from having too large an influence. Figure A1 below shows the CDFs before and after weighting has been applied.

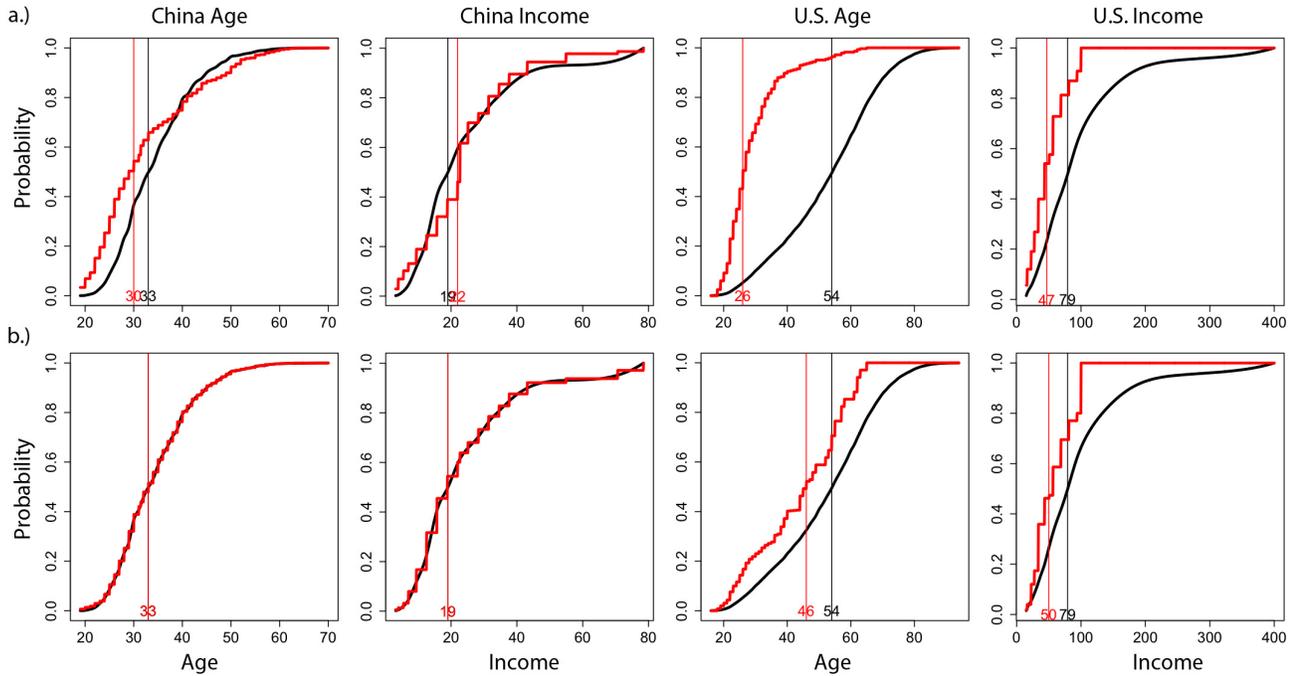


Figure A1: Age and income cumulative distribution functions in China and the U.S. of our survey sample (red) and Ford's survey sample (black) before weighting (a.) and after weighting (b.). Median values are given as vertical lines in each figure.

Market Simulations

To estimate the market simulations in section 3.4, we use the estimated mean and standard deviation coefficients from model 2 to draw population-level coefficients. To account for uncertainty in these estimated coefficients, we take multiple draws of the model coefficients drawn from the variance-covariance matrix of the estimated model. For each set of drawn coefficients, we use the simple logit probabilities in equation 3.2 to calculate the expected market share of a plug-in vehicle against its gasoline counterpart. We then take the mean of these shares as one data point, and then repeat the simulation again using a different set of drawn. We use these data points across 1,000 draws to estimate a mean and 95% confidence interval on the shares. The attribute levels of the vehicles compared in these simulations are shown below in Table A8.

Table A8: Vehicle attribute values used in market simulations

Brand	Model	Technology	Price (\$1,000)	U.S. Operating Cost (U.S. cents/mile)	China Operating Cost (U.S. cents/mile)	0-60 mph acceleration time (sec)
Toyota	Prius	PHEV ₁₀	32	4.7	5.7	10.9
	Prius	HEV	25	7.4	8.9	9.7
Ford	C-Max	PHEV ₂₀	33	5.3	6.4	8.9
	C-Max	HEV	26	8.8	10.6	9.4
BYD	F3DM	PHEV ₄₀	21	8.0	9.7	10.5
	F3	CV	8	12.0	14.5	11.8
Chevrolet	Volt	PHEV ₄₀	41	3.9	11.2	8.9
	Cruze Eco	CV	19	11.9	14.4	10.2
Nissan	Leaf	BEV ₇₅	35	3.7	4.5	7.9
	Versa	CV	16	12.3	14.9	9
Ford	Focus	BEV ₁₀₀	40	3.5	4.3	9.6
	Focus	CV	19	11.9	14.4	8.3

A.3 Field Experiment Setup and Procedure

Experiment Setup & Fielding

The choice experiment survey was fielded in both China and the U.S. The surveys were equivalent in content and in presentation except for (1) translation, which was conducted by the State Information Center in Beijing, China, and then back translated for verification by a third party expert and (2) the values of some attributes, which were each calibrated to the values in the corresponding existing vehicle market, as discussed in section A.6. The surveys were fielded in China during July and August of 2012 and in the U.S. in September 2012 and February 2013.

In China, the surveys were conducted in-person using laptop computers in the following four major cities chosen for their large passenger vehicle markets as well as geographic representativeness: Beijing, Shanghai, Shenzhen, and Chengdu. In each city a private market research company (arranged by the State Information Center) provided the staff as well as expertise in choosing locations to administer the survey. The survey location in each city was chosen for its proximity to automobile dealerships representative of the current automobile market. John Helveston personally oversaw all survey fielding in each city except for the last few days of fielding in Beijing, as a record-breaking flood interrupted the fielding schedule (a member of the SIC oversaw the final days of fielding in Beijing). Fielding took 3-4 days in each city, and was conducted from Thursday to Sunday of the week, as these were busier vehicle shopping days. Respondents were approached at random and asked if they had recently purchased or were interested in purchasing soon a car or SUV. If so, they were further asked if they were interested in taking a short 10-15 minute survey, for which they would be compensated with a small gift.

In the U.S., the survey was fielded online using Amazon Mechanical Turk (AMT). An initial pool of recent or potential vehicle buyers was found through a short survey that asked about recent or future purchases, and then the full conjoint survey was sent to those who qualified as recent or future vehicle buyers (i.e. selected “car” or “SUV” as a recent or future purchase on the screener survey). Each AMT respondent was compensated with \$2 for completing the survey.

In both surveys, respondents were thrown out if they completed the survey in under 6 minutes (as this was found to be a natural cutoff time for completing the survey without randomly answering the choice questions), or if they failed to choose the dominant example choice question which was fixed for each respondent (indicating that the respondent either misunderstood the task or did not pay close attention to the choice question).

Experiment Procedure - China

1. Arrive at survey location, setup laptop computers and boot up survey software.
2. Team members walk around the streets nearby survey location and ask any individual walking by if they recently purchased a vehicle or are planning to purchase one soon.
3. If a respondent says yes to either question in step 2, then the team member asks the respondent if he or she would like to take a survey, explaining it is for university research and that we will provide a small gift.
4. The respondent is seated at a laptop and instructed how to take the survey.
5. While the respondent fills out the survey, a team member sits beside only to answer any misunderstandings.¹
6. At completion of the survey, the respondent is given a small gift and thanked for participating.

Experiment Procedure – U.S.

1. A small survey is fielded on Amazon Mechanical Turk (AMT) available to all AMT users. It asks some demographic information as well as two questions about recent or future purchases, and users are paid \$0.10 each for completing the survey.
2. If an AMT user selects “personal vehicle” as a recent or future purchase, he or she is tagged as a “car buyer.”
3. The full survey is fielded on AMT to all AMT users tagged as a “car buyer.”
 - a. A “HIT” is posted on AMT announcing the survey, which includes a link to the survey hosted on an external website.

¹ Team members rarely had to explain any information about the survey, and primarily just encouraged the respondents to continue on in the survey and to avoid quitting early.

- b. Respondents click the link and complete the survey on the external website.
- c. At the end of the survey, respondents are provided with a unique completion code which they must copy and paste into the HIT back on AMT.
- d. Once the completion codes entered in the HIT are matched to the survey (confirming completion), respondents are paid \$2.00 through the AMT portal.

A.4 Field Experiment Questionnaire (English)¹

¹ The Chinese version of the questionnaire was identical in presentation and content except for translation, which was conducted by the State Information Center in Beijing, China, and then back translated for verification by a third party expert. The attribute levels and units were also adapted for the Chinese market.

CONSENT FORM

This survey is part of a research study conducted by Erica Fuchs, Ph.D. and Jeremy Michalek, Ph.D. at Carnegie Mellon University.

The purpose of the research is to develop a methodology to assess the impact of nation-specific differences in market and production characteristics on the relative competitiveness of emerging technologies and global technology trajectories.

Procedures

We will conduct Conjoint Surveys to assess consumer preference for vehicle attributes in the U.S. and in China. Respondents will be asked to fill out a short conjoint survey where they are shown hypothetical vehicle profiles and asked to choose which they prefer. The survey is anticipated to take 10 to 15 minutes to complete.

Participant Requirements

Participation in this study is limited to individuals age 18 and older.

Risks

The risks and discomfort associated with participation in this study are no greater than those ordinarily encountered in daily life, during other online activities, or when evaluating purchase decisions when shopping for a car.

Benefits

There may be no personal benefit from your participation in the study but the knowledge received may be of value to humanity.

Compensation & Costs

There will be no costs for participating. You will be paid \$2 for completing the survey.

Confidentiality

The data captured for the research does not include any personally identifiable information about you.

Right to Ask Questions & Contact Information

If you have any questions about this study, you should feel free to ask them by contacting the Principal Investigator now at erhf@andrew.cmu.edu. If you have questions later, desire additional information, or wish to withdraw your participation please contact the Principle Investigator by mail, phone or e-mail in accordance with the contact information listed above.

If you have questions pertaining to your rights as a research participant; or to report objections to this study, you should contact the Research Regulatory Compliance Office at Carnegie Mellon University.

Email: irb-review@andrew.cmu.edu. Phone: 412-268-1901 or 412-268-5460

The Carnegie Mellon University Institutional Review Board (IRB) has approved the use of human participants for this study.

Voluntary Participation

Your participation in this research is voluntary. You may discontinue participation at any time during the research activity.

The following questions will be included in the web page so that they must be answered appropriately before the individual can proceed to the study task:

1. I am age 18 or older. Yes No [if the answer is no, the individual cannot participate and should not be allowed to proceed to the next question.]
 2. I have read and understand the information above. Yes No [if the answer is no, the individual cannot participate and should not be allowed to proceed to the next question.]
 3. I want to participate in this research and continue with the survey. Yes No [if the answer is no, the individual cannot participate and should not be allowed to proceed to the next question.]
-

Section 1

We will begin the survey by asking about your vehicle history and interest in purchasing a car.

1. When was the last time you purchased a vehicle?
 Never Less than 1 year ago Greater than 1 year ago
2. When do you plan on purchasing a vehicle in the future?
 Never Less than 1 year from now Between 1 and 2 years from now Greater than 2 years from now
3. In your household, who is the primary decision-maker for purchasing a vehicle?
 Me Another household member Both me and another household member together

-- Page 2 --

Section 1

4. What was the make and model of the last vehicle you purchased?

Make: _____

Model: _____

(leave blank if you do not currently own a vehicle)

5. How many vehicles does your household currently own?
 0 1 2 3 or more
6. On average, how many miles do you drive every day?
 Less than 5
 5 to 10
 10 to 15
 15 to 20
 20 to 25
 25 to 30

- 30 to 35
- 35 to 40
- More than 40
- I don't know
- I don't drive

7. How many total miles did you drive last year?

- Less than 5,000
- 5,001 to 7,000
- 7,001 to 9,000
- 9,001 to 11,000
- 11,001 to 13,000
- 13,001 to 15,000
- 15,001 to 17,000
- 17,001 to 19,000
- More than 19,000
- I don't know
- I don't drive

-- PAGE 3 --

Section 2

From this point in the survey forward, you should consider everything shown as though you were shopping for your next primary vehicle.

-- PAGE 4 --

Section 2

If you were shopping for a car, which car segment would you be most interested in purchasing?
(some pictures are presented as examples):

- Small Cars:**
- Midsized Cars:**
- Large Cars:**
- None of the above**

-- PAGE 5 --

Section 2

Of the segment you chose, which vehicle would you be most likely to buy based on appearance only?

-- PAGE 6 --

Section 2

You have selected this vehicle design:

[image of chosen design here]

This image will be used for the next section. If the vehicle shown above is not the one you wanted, click the "back" button on the web browser and select a different image, otherwise click "next" below.

-- PAGE 7 --

Section 3

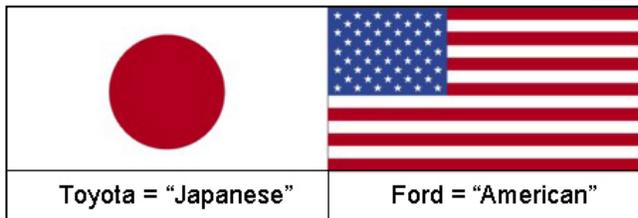
In the next section, we will ask some questions about certain vehicle features, explained below. Please read the descriptions carefully before moving forward in the survey. You will be able to view a summary of these descriptions later in the survey.

Price



The final price paid for the vehicle in dollars, including all taxes and fees.

Brand



The vehicle manufacturer country of origin.

Vehicle Type

Conventional: Gasoline engine only.



Hybrid: Smaller gasoline engine + electric motor + small battery.



Gasoline engine recharges the battery, fuel consumption is reduced.

Plug-In Hybrid



Hybrid that can also be plugged into an electrical outlet to charge the battery. Runs on electricity for a short range (10 – 40 miles), then switches to gasoline.

Electric:



Electric motor only. Must be plugged into an electrical outlet to be refueled. (6 – 10 hours to fully charge).

Fast Charging Capability



If this feature is available, an electric vehicle could fully charge in 10 – 20 minutes, but only at special service stations.

Fuel Cost



Cost in cents per mile driven. The equivalent fuel efficiency in miles per gallon (MPG) of a conventional gasoline vehicle is displayed in parenthesis.

Acceleration Time



The acceleration time to go from 0 to 60 mph, such as when entering a highway or interstate.

-- Page 8 --

Section 3

For the next section, we will show you 3 vehicles for sale, and you should select the choice you are most likely to buy, assuming they are the only available choices on the market.

Each option will look the same, but will have different attributes. Below is an example question.

Note that some of the options are likely to be vehicles you have not seen in the current market, but may become available in the future. You should respond as if they were available today.

**** BEGIN EXAMPLE QUESTION ****
[example question here]

-- PAGE 9 --

Section 3

Great! We will now begin the comparison portion of the survey. You will be asked 15 questions total in this section. You may proceed now by clicking the “next” button below.

-- PAGE 10 --

Section 3

Suppose these 3 vehicles below were the only vehicles available for purchase, which would you choose?

Each option will look like this:

Attribute Option 1 Option 2 Option 3

*To view an attribute description, click on:

**The average acceleration for cars in the U.S. is 0 to 60 mph in 7.4 seconds

[Here each random question was displayed in sequential order]

-- Page 11 --

Section 4

We will now ask some general questions about your vehicle preferences and experience with alternative vehicles

1. Please rate the importance of these features in making a decision to purchase a vehicle:

	Unimportant	Somewhat Unimportant	Neutral	Somewhat Important	Very Important
Price					
Storage / cargo space					
Reliability / low maintenance					
Safety					
Vehicle towing capacity					
Outer appearance / style					

2. Please rate how much you agree with the following statements:

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
The appearance of my vehicle is an important status symbol for me					

I want people to know that I am an environmentally friendly person					
Global climate change is a serious threat to humanity					
Global climate change is mostly caused by human activities					

3. Please select any of the vehicle types that you have ever driven, even if for just a test drive:

- Conventional
 Hybrid
 Plug-in Hybrid
 Electric
 I have never driven any of these vehicle types

4. Please select how many parking spaces you have to park a vehicle at the following locations:

At home in my personal garage:

- 1
 2
 3
 4
 5 or more
 I don't know

At home in a community parking garage:

- 1
 2
 3
 4
 5 or more
 I don't know

At home in my driveway:

- 1
 2
 3
 4
 5 or more
 I don't know

At home on the street:

- 1
 2
 3
 4
 5 or more
 I don't know

At home at another location:

- 1
 2
 3
 4
 5 or more
 I don't know

5. Of the places you have available parking, which have access to an electric outlet where you could plug in a vehicle for charging? (select all that apply)

- At home in my personal garage
 At work in a community parking garage
 At home in a community parking garage
 At work in my driveway
 At home in my driveway
 At work on the street
 At home on the street
 At parking meters in town
 At home at another location

6. Do you have access to fast charging stations in your city?

- Yes
 No
 I don't know

7. Please rank your top 3 favorite vehicle brands starting from "1" as most favorite:

#1:

#2:

#3:

8. Which vehicle type do you expect will have highest maintenance cost?

- Conventional
 Hybrid
 Plug-in Hybrid
 Electric
 All about the same

Section 5

Thank you so much for your help. Please answer these last few demographic questions for statistical purposes and then we'll be finished. Your responses will be kept confidential, and we have designed the survey such that there is no way to identify you to your responses.

1. What is your annual household income range?

- Less than \$12,500
- \$12,500 to \$19,999
- \$20,000 to \$24,999
- \$25,000 to \$29,999
- \$30,000 to \$37,499
- \$37,500 to \$49,999
- \$50,000 to \$62,499
- \$62,500 to \$74,999
- \$75,000 to \$87,499
- \$87,500 to \$99,999
- \$100,000 or more
- I do not wish to answer

2. What is your sex?

-
- Male Female I do not wish to answer

3. Including yourself, how many people are in your household?

-
- 1 2 3 4 5 6 7 or more I do not wish to answer

4. In what year were you born: _____

5. Please enter your zip code: _____

6. Which of the following best describes your highest achieved education level?

- Some secondary education
- Graduated high school
- Some university Education
- 2 year university or trade school degree
- 4 year university degree (bachelors)
- Masters degree
- Doctoral degree
- I do not wish to answer

7. How many children do you have?

-
- 1 2 3 4 5 6 or more I do not wish to answer

8. Could you tell us what your current living situation is?

- Married or living with a partner
- Separated
- Divorced
- Widowed
- I do not wish to answer

9. Please share your comments on the survey design:

-- Page 13 --

This completes the survey. Thank you!

-- Page 14 --

A.5 Details of Survey Design and Preparation

The survey design process began in the spring of 2011. John Helveston was interning in Beijing, and during this time he visited several automotive dealerships and conducted informal interviews with salesmen to identify which vehicle attributes were most important to consumers. In addition, a review of previous literature revealed attributes that have been shown to be important in vehicle choice, as shown in Table A9 below. The results of the interviews and literature review were used to narrow the attribute list included in the choice survey.

Table A9: Important attributes for vehicle choice from previous literature.

Study	Price	Brand	Type	Charge Time	Efficiency	Acceleration
Train	x	x	x	x	x	x
Brownstone	x		x	x	x	x
McFadden	x	x	x		x	x
Golob	x		x		x	
Axsen	x	x	x	x	x	x

Once the attributes were chosen, we had to choose levels for each, which required considering the interests of the study as well as characteristics of the U.S. and Chinese vehicle markets. For vehicle type, we used a CV, a HEV, 3 PHEVs, and 3 BEVs (each with different electric ranges). These were chosen because we needed to compare preferences for electrified vehicle types against CVs and we also wanted to compare the effect of AER for BEVs and PHEVs on preferences. We chose 3 BEVs and 3 PHEVs as a compromise between the number of attributes we would need to estimate and the ability to estimate the effect of AER. We did not want to include Brand originally as we were afraid it might “swamp” the effects of other attributes and because we were not particularly interested in its effect on vehicle choice, but previous interviews suggested that without it respondents would likely not take the survey seriously as brand is such an important factor. As a result, brand was represented as the country of origin of the make (ex. “Volkswagen” would be “German,” and “Ford” would be “American”) in order to maintain a manageable number of alternatives. We originally had 3 levels for “fast charging” times (10, 20, and 30 minutes) and 3 levels for “slow charging” times (4, 6, and 10 hours) that were used in several pilot studies, but we found no significance in any of these attributes, so we ended up using only a “Fast Charging Capability” attribute, which was a binary attribute for whether or not a PEV had the ability to charge in under 15 minutes. Since fuel prices are different in each country and the mixed vehicle types in the survey have different fuels (gasoline and electricity), operating cost was presented in cost per mile driven rather than presenting

vehicle efficiency. The equivalent fuel economy for a conventional gasoline vehicle was provided in parenthesis for reference, since it is a more familiar metric for respondents, a result of feedback from the pilot studies. Finally, the acceleration time attribute was simply the time it took to accelerate from 0 to 60 miles per hour in the U.S. or 0 to 100 kilometers per hour in China.

For purchase price, operating cost, and acceleration time, the levels were different between each country as well as between cars and SUVs because this is more reflective of what is available in the real market. The levels for these attributes were chosen based on the respective sales distributions of currently available vehicles in the market in 2011 to represent the range of attributes relevant for each market. In each case, we plotted the histogram of the sales data and used approximately the 5th, 25th, 50th, 75th, and 95th percentile values from the resulting distribution as the levels for the attribute. Figure A2 below illustrates an example for car prices in China.

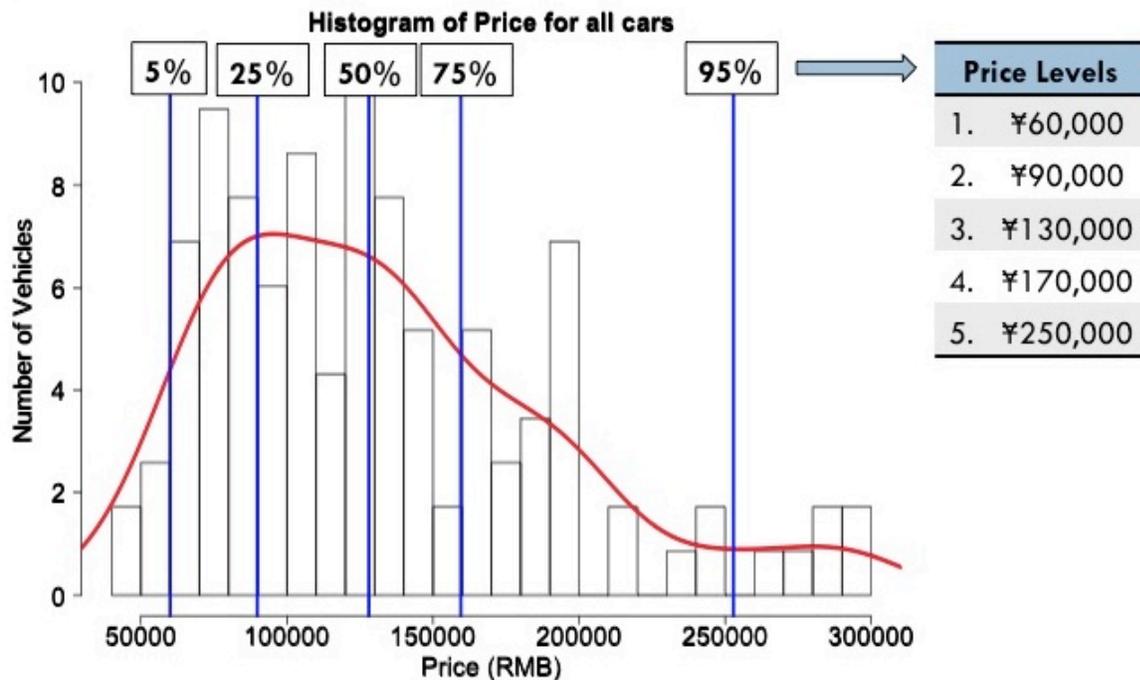


Figure A2: Histogram of prices for new cars in China in 2011, with percentiles indicating how the 5 price levels for the China survey were chosen.

第三部分

各款型的外观如下:



假设只能选择购买下面3款车中的一款，您会选择哪一款？

属性*	款型 1	款型 2	款型 3
车辆类型 ^①	传统汽车  一罐汽油可开450公里	插电式混合动力汽车  &  第一个 65公里使用电力 (一罐汽油可开450公里)	电动汽车  满电可开120公里
价格 ^①	90,000 元	170,000 元	130,000 元
品牌 ^①	德国	美国	日本
快速充电能力 ^①	没有	没有	有
燃料成本 ^①	0.61元/公里 (8.0升/100公里)	0.42元/公里 (5.5升/100公里)	0.34元/公里 (4.5升/100公里)
0至100公里/时加速时间** ^①	13秒 (一般慢)	13秒 (一般慢)	11秒 (一般快)
	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

*了解某一属性的详细描述，请点击: ^①

**中国汽车平均加速在12.4秒内0-100公里/时。

Figure A3: Example choice task for China. The attribute values (levels) in each choice task were randomly assigned for each question and each respondent.

In an attempt to make the survey as realistic to a true purchase situation as possible, we considered displaying the attributes and levels in the survey in the same manner as the fuel economy labels in each country. Figure A4 and Figure A5 are example images of the current labels in the U.S. and China. While perhaps a better representation of reality, we decided against this option in favor of a simple table of the attributes because the information on the labels in each country is so different and because not all of the attributes in our study are on each label.

EPA Fuel Economy and Environmental Comparisons

Dual Fuel Vehicle:
Electricity-Gasoline

Charge Time

4 hours
@240V

All Electric

When battery is fully charged, first **35** miles only.

93 MPG equivalent
combined city/hwy **36** kW-hrs per 100 miles

\$601 cost per year if always run in All Electric

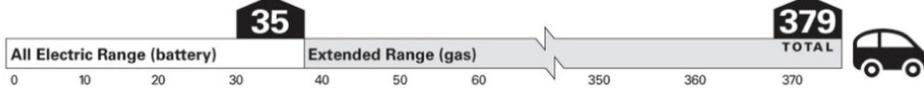
Gas Only

When electricity is used up, runs on gas for another **344** miles.

37 MPG
combined city/hwy **2.7** gallons per 100 miles

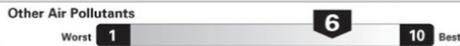
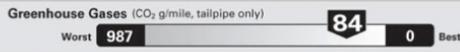
\$1,302 cost per year if always run in Gas Only mode

Range (Miles)



How This Vehicle Compares (combined composite)

Among all vehicles and within compact cars



Examples: Charging Routines

Miles driven between full charge	Fuel Economy MPG	Electricity Consumed	Electricity + Fuel Energy Cost
30	NA	10.9 kWh	4¢ / mi
45	168	12.9 kWh	5¢ / mi
60	89	12.9 kWh	6¢ / mi
75	69	12.9 kWh	7¢ / mi
Never Charge	37 city / 40 hwy	N/A	9¢ / mi

Your actual mileage and costs will vary with fuel cost, temperature, driving conditions, and how you drive and maintain your vehicle. Cost estimates are based on 15,000 miles per year at \$3.20 per gallon and 11 cents per kW-hr. MPG equivalent: 33.7 kW-hrs = 1 gallon gasoline energy.

Visit www.fueleconomy.gov to download the Fuel Economy Guide (also available at dealers).



Figure A4: Example U.S. EPA fuel economy label.

企业标志
Company Logo

中国汽车燃料消耗量标识

CHINA AUTOMOBILE FUEL CONSUMPTION LABEL

<p>生产企业: Manufacturing Company</p> <p>车辆型号: Vehicle Model</p> <p>发动机型号: Engine Model</p> <p>排量: Engine Capacity (liters)</p> <p>变速器类型: Transmission Type</p> <p>整备质量: Curb Weight</p> <p>其它信息: Other Information</p>	<p>Contact Person: 联系人: 谭志国</p> <p>Phone: 手机: 13401103978</p> <p>燃料种类: Fuel Type</p> <p>额定功率: Rated Power</p> <p>驱动型式: Drive Type</p> <p>最大总质量: Max Weight</p>
--	--

Urban (city) Fuel Economy

市区燃料消耗量: XX.X l/100km

Combined Fuel Economy

综合燃料消耗量: **XX.X** l/100km

Extra-urban (high way) Fuel Economy

市郊燃料消耗量: XX.X l/100km

Acceptable Fuel Consumption Limits

GB 19578-2004 限值要求

1st Stage Requirements 第一阶段限值: X.X l/100km

2nd Stage Requirements 第二阶段限值: X.X l/100km

说明 Explanation

本标识所采用的燃料消耗量数据系根据 GB/T 19233-2003 《轻型汽车燃料消耗量试验方法》规定的行驶工况测定。

由于驾驶习惯、道路状况、气候条件和燃料品质等因素的影响，实际燃料消耗量通常高于本标识的燃料消耗量。

联系人: 谭志国 手机: 13401103978

Figure A5: Example Chinese fuel economy label (with English translations).

A.6 Government Support for Vehicle Electrification in the U.S. and China

In the U.S., interest in vehicle electrification grew out of growing energy concerns following the 1970s and 1980s energy crises as well as the zero-emissions vehicle mandate set by the California Air Resources Board in 1990. Federal tax credits for new qualified plug-in electric vehicles, including BEVs and PHEVs, were granted under the American Recovery and Reinvestment Act of 2009. The federal credit for new PEVs is worth \$2,500 plus \$417 for each kilowatt-hour of battery capacity over 5 kWh. The total maximum allowable credit is \$7,500 (U.S. Congress, 2009). In China, the government's 12th five-year plan targets PEV ownership and domestic production of one million electric vehicles in 2015. For all domestically produced PEVs, the government currently waives the 9% sales tax and provide subsidies of RMB 3,000 (\$470) per kWh of battery capacity with a maximum of RMB 60,000 (~\$9,420) for BEVs and RMB 50,000 (~\$7,850) for PHEVs (State Council, 2012). Figure A6 below summarizes the national incentives in place in each country.

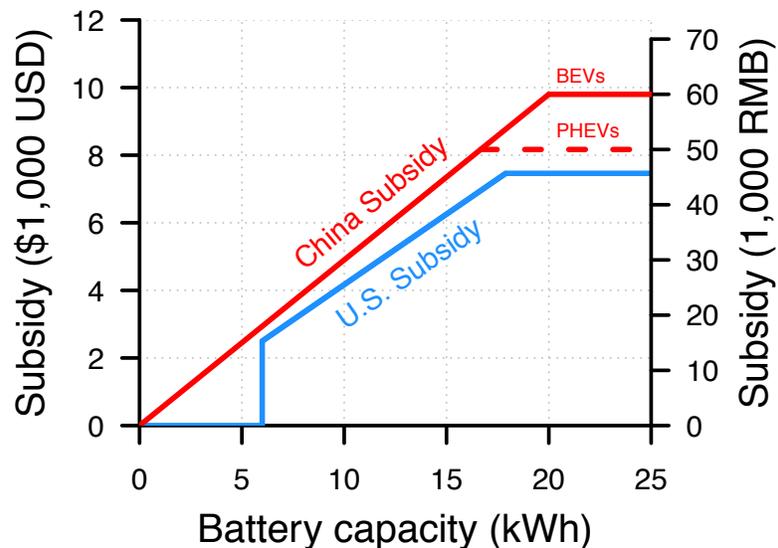


Figure A6: PEV Subsidies in the U.S. and China versus battery capacity.

Appendix B

Supplemental Information for Chapter 4

B.1 Data Set Characteristics and Information

A number of characteristics influence the amount of information a data set carries about the unknown model parameters. In particular, we examine the relationships between the Fisher Information and the number of observations, the correlation among observed attributes, the number of different choice sets, and the number of alternatives in the choice sets. To illustrate these relationships, we simulate sets of choice data for a simple two product case and then compute the determinant of the information matrix at the true parameters. By varying one characteristic while holding all others constant, we can visualize the relationships between these attributes and data set information, as shown in Figure B.1. We use the determinant of the information matrix as an approximation for the overall total amount of information in a data set.

The amount of information is quadratically related to the number of choice observations (Figure B.1a), making sample size a large determinant of the overall amount of information. Increasing the number of alternatives in a choice set (Figure B.1b) has diminishing returns on information and follows a logarithmic relationship. As Figure B.1c illustrates, the correlation between attributes in the data set is critical. While low correlations have a limited impact on information, highly correlated attributes can dramatically reduce the level of information. Finally, increasing the number of choice sets in a data set, which is the same as adding more variation among the attributes,

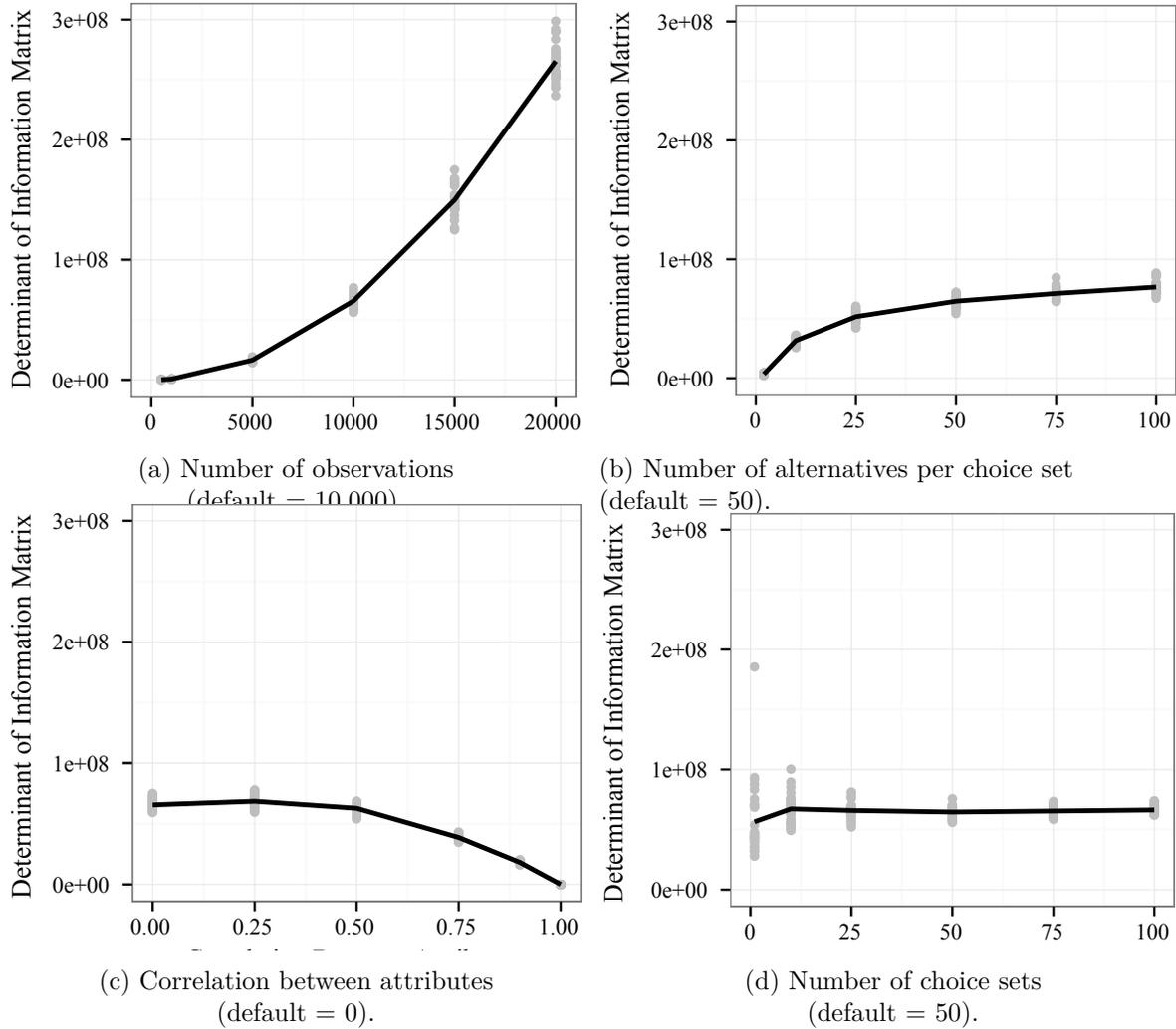


Figure B.1: Relationships between data set characteristics and Fisher Information.

does not necessarily affect the overall *amount* of information but rather the *variation* in the amount of information. As Figure B.1d shows, a low number of choice sets results in high variation in the amount of information (depending on the random draw of data), but as the number of choice sets increases the amount of variation among the attributes also increases which decreases the variation in the information. Taking all of these factors together illustrates how some data sets (such as aggregate market data with highly correlated attributes) can be relatively uninformative about attributes even with large sample sizes.

B.2 Sensitivity Analysis Figures

This section provides plots of each sensitivity case in Table 4.5. For each sensitivity case, we plot the WTP parameters as box plots as well as the LR test rejection rates as bar plots. In each plot, the light colors represent the base case and the dark colors represent the sensitivity case. Table B.1 below shows the sensitivity ranges examined for each variable as well as the figures associated with each sensitivity case.

Table B.1: Sensitivity cases

Parameter	Base Case	Sensitivity Case	Figure Numbers
λ^R	1	0.1	Figures B.2 - B.3
		5	Figures B.4 - B.5
λ^S	1	0.1	Figures B.6 - B.7
		5	Figures B.8 - B.9
β^R	1	-3	Figures B.10 - B.11
		3	Figures B.12 - B.13
ζ	1	-1.5	Figures B.14 - B.15
		1.5	Figures B.16 - B.17
ρ_{px}	0	0.5	Figures B.18 - B.19
N^R	1000	500	Figures B.20 - B.21
		5000	Figures B.22 - B.23
N^S	2000	500	Figures B.24 - B.25
		5000	Figures B.26 - B.27
A^R	15	3	Figures B.28 - B.29
		100	Figures B.30 - B.31
A^R	3	2	Figures B.32 - B.33
		10	Figures B.34 - B.35
T^R	50	1	Figures B.36 - B.37
		200	Figures B.38 - B.39

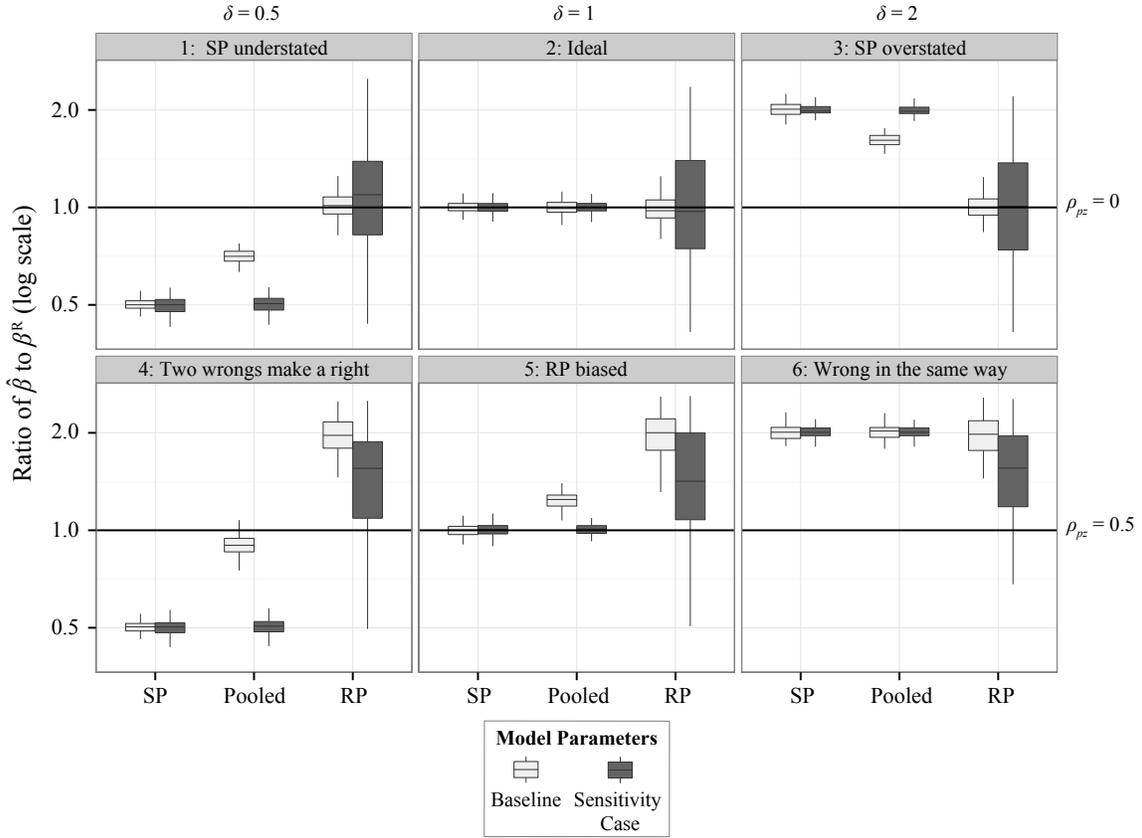


Figure B.2: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $\lambda^R = 0.1$. Each box plot represents results from 100 simulated data sets.

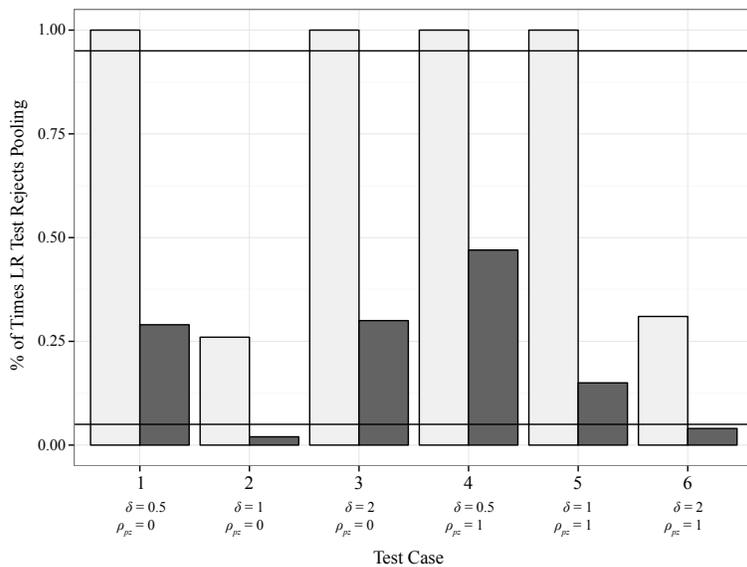


Figure B.3: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $\lambda^R = 0.1$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

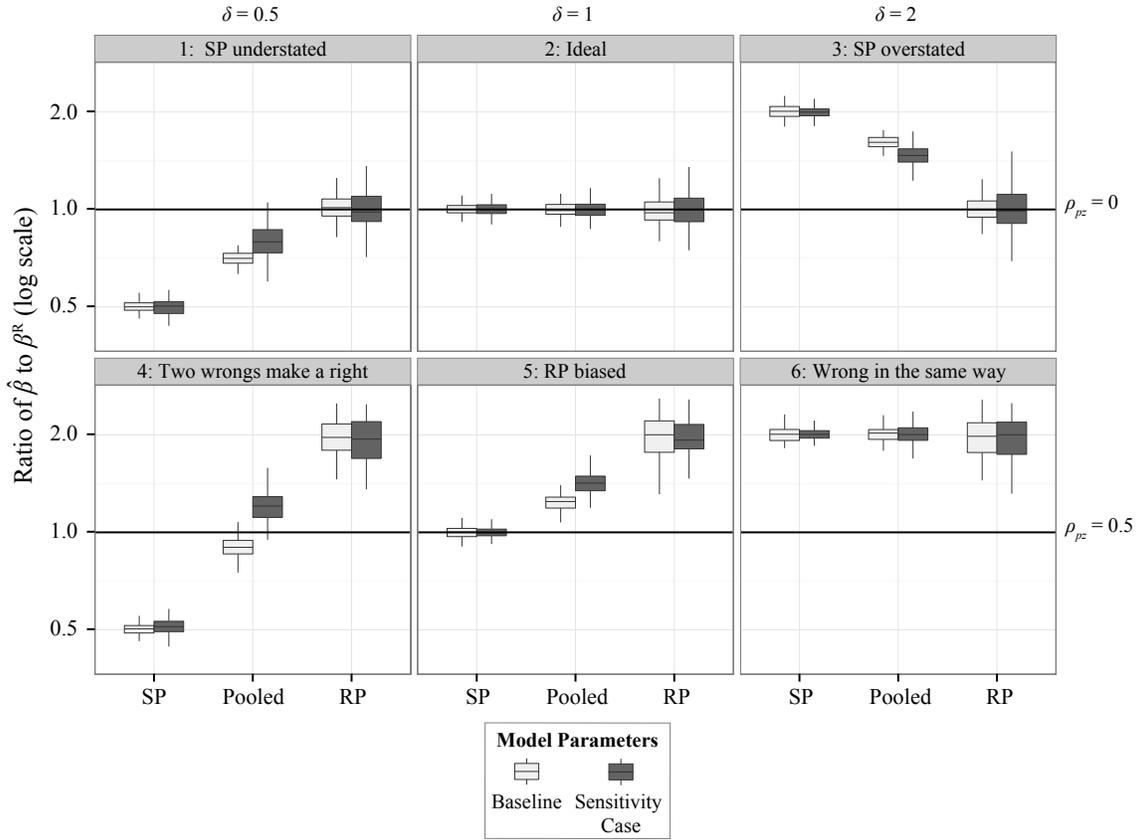


Figure B.4: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $\lambda^R = 5$. Each box plot represents results from 100 simulated data sets.

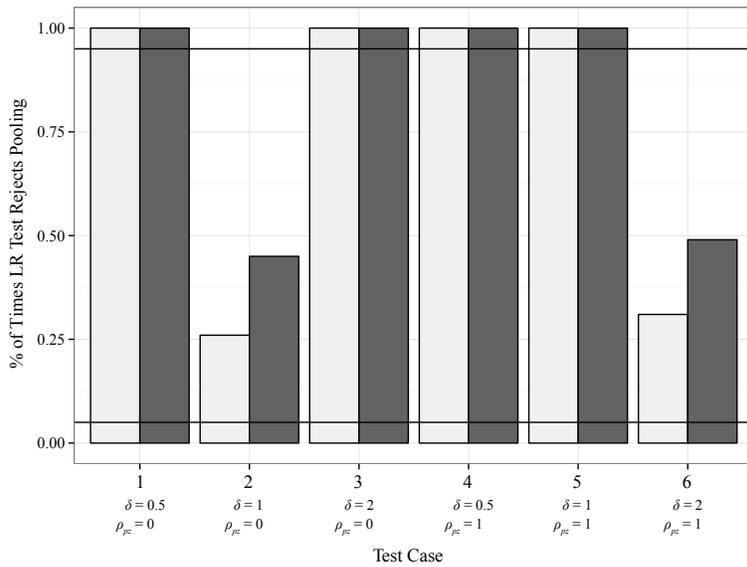


Figure B.5: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $\lambda^R = 5$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

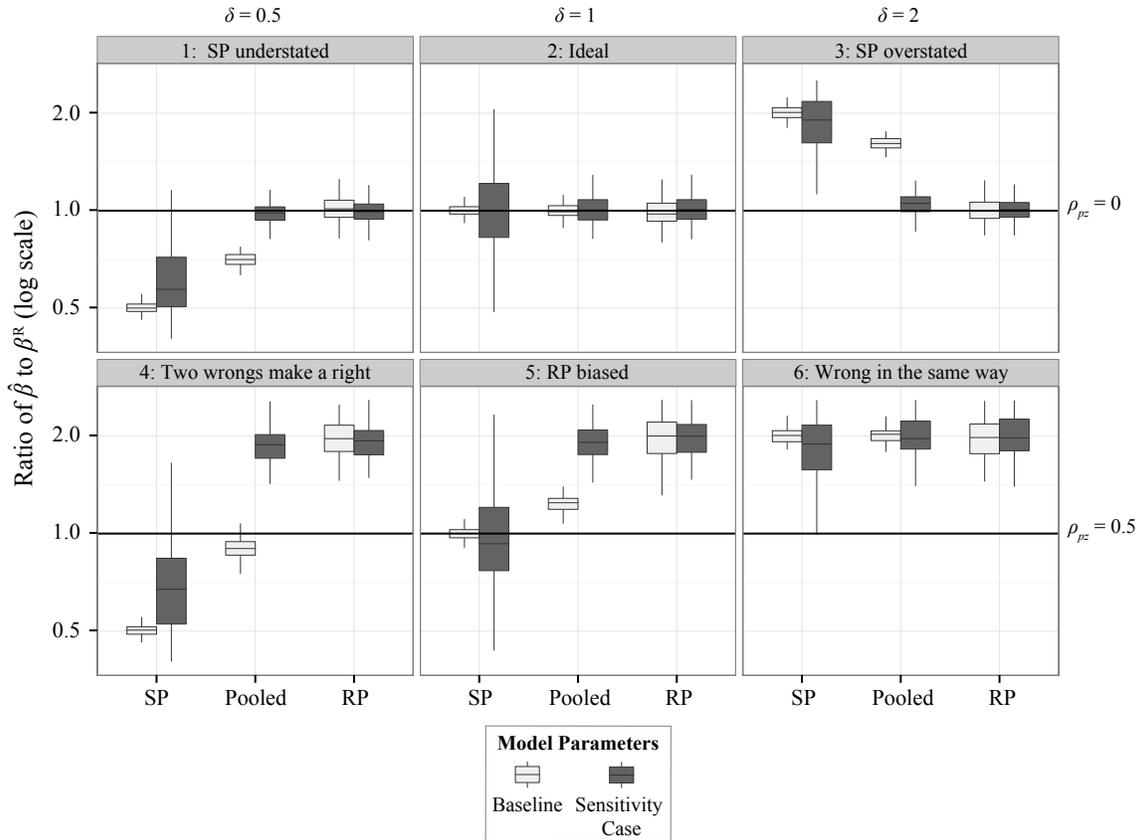


Figure B.6: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $\lambda^S = 0.1$. Each box plot represents results from 100 simulated data sets.

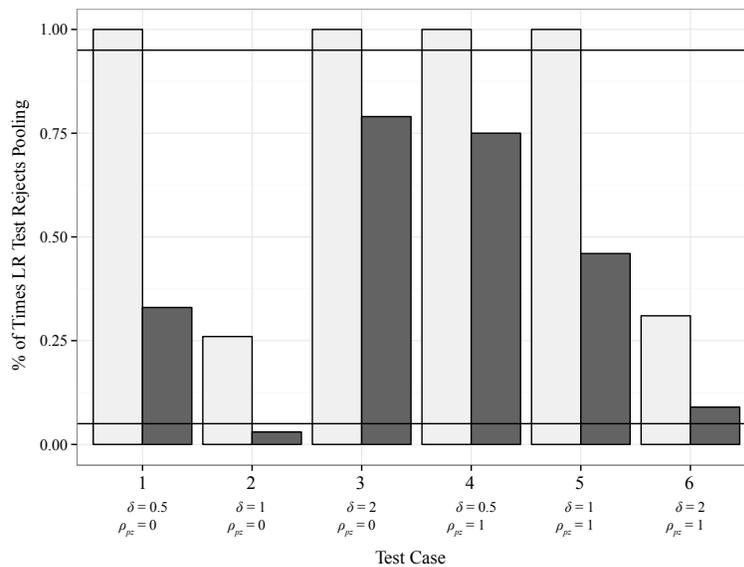


Figure B.7: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $\lambda^S = 0.1$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

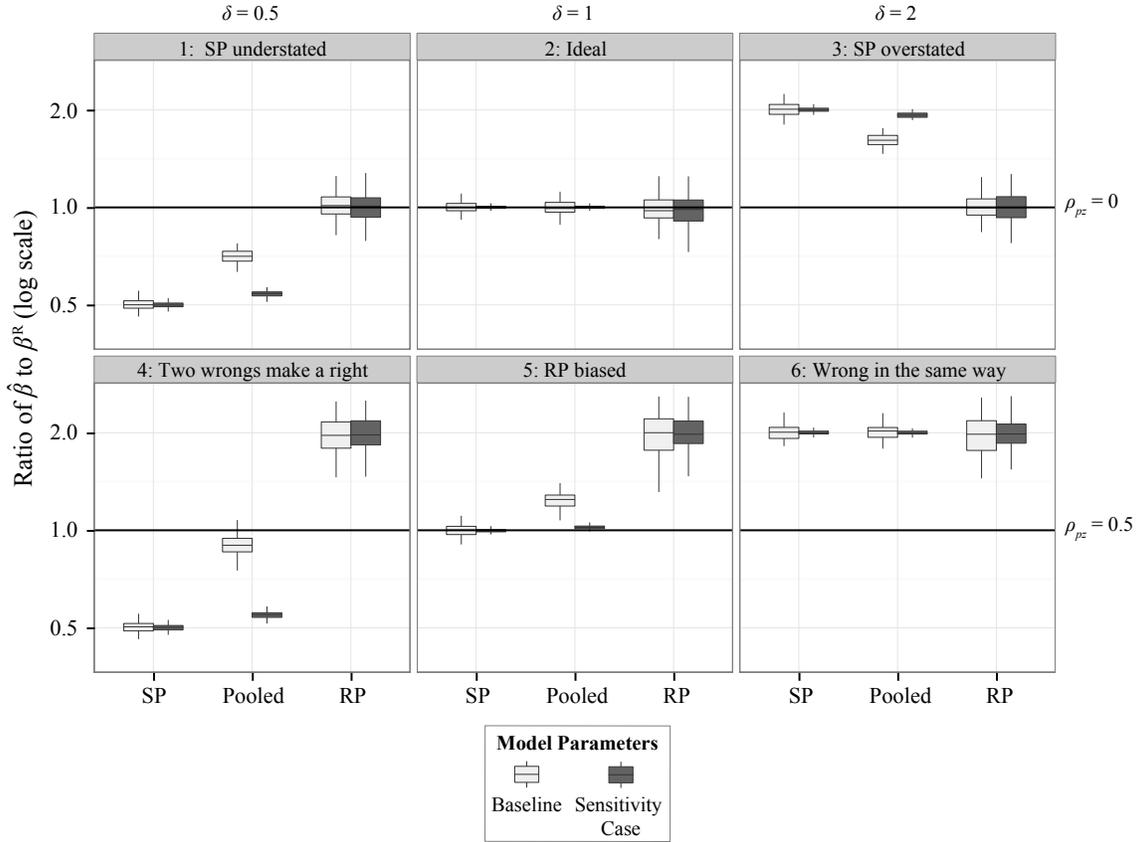


Figure B.8: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $\lambda^S = 5$. Each box plot represents results from 100 simulated data sets.

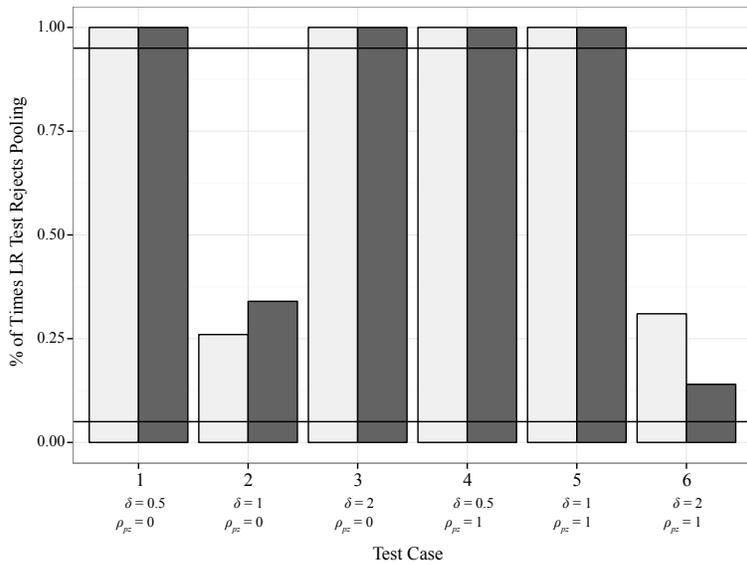


Figure B.9: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $\lambda^S = 5$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

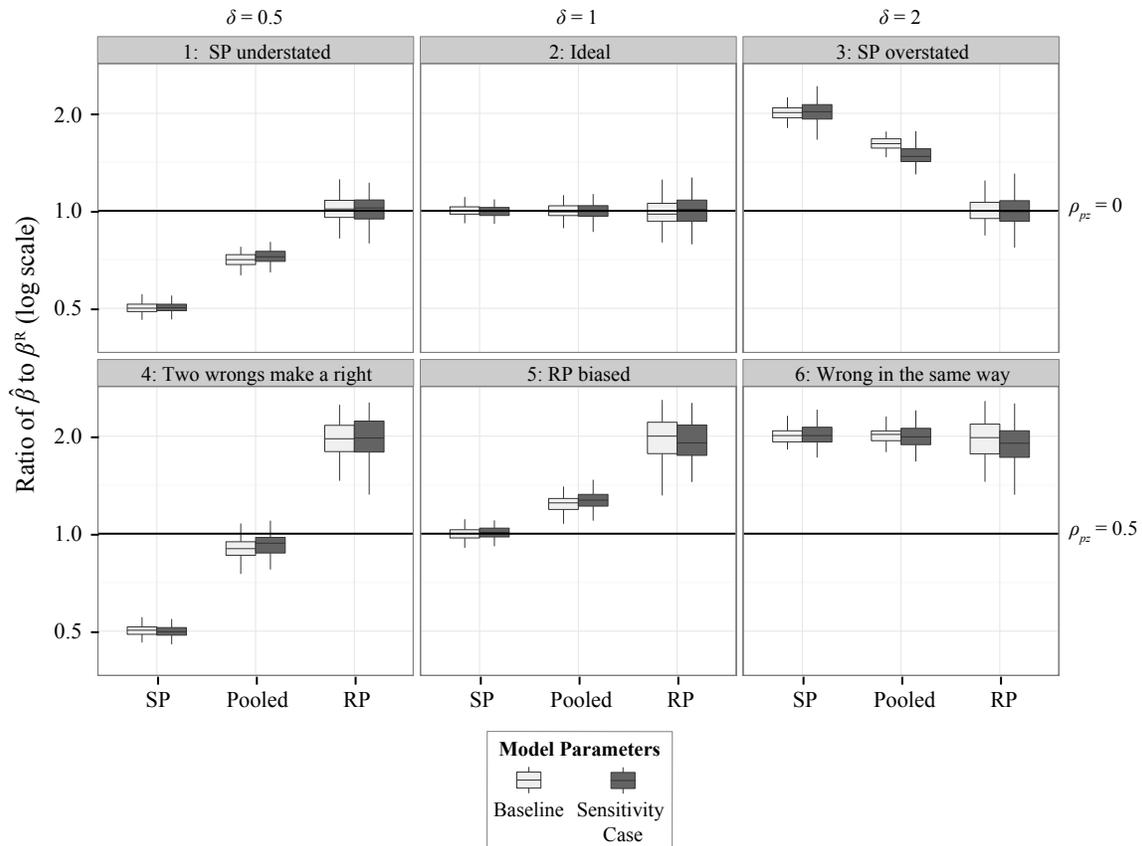


Figure B.10: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $\beta^R = -3$. Each box plot represents results from 100 simulated data sets.

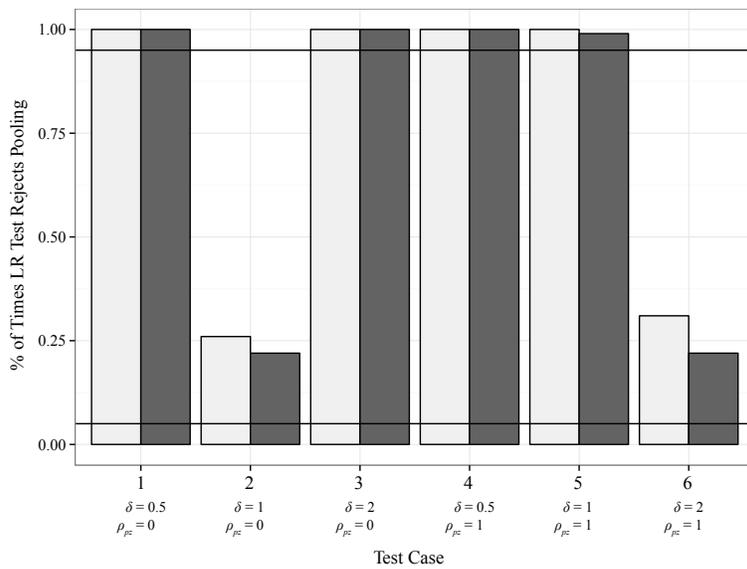


Figure B.11: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $\beta^R = -3$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

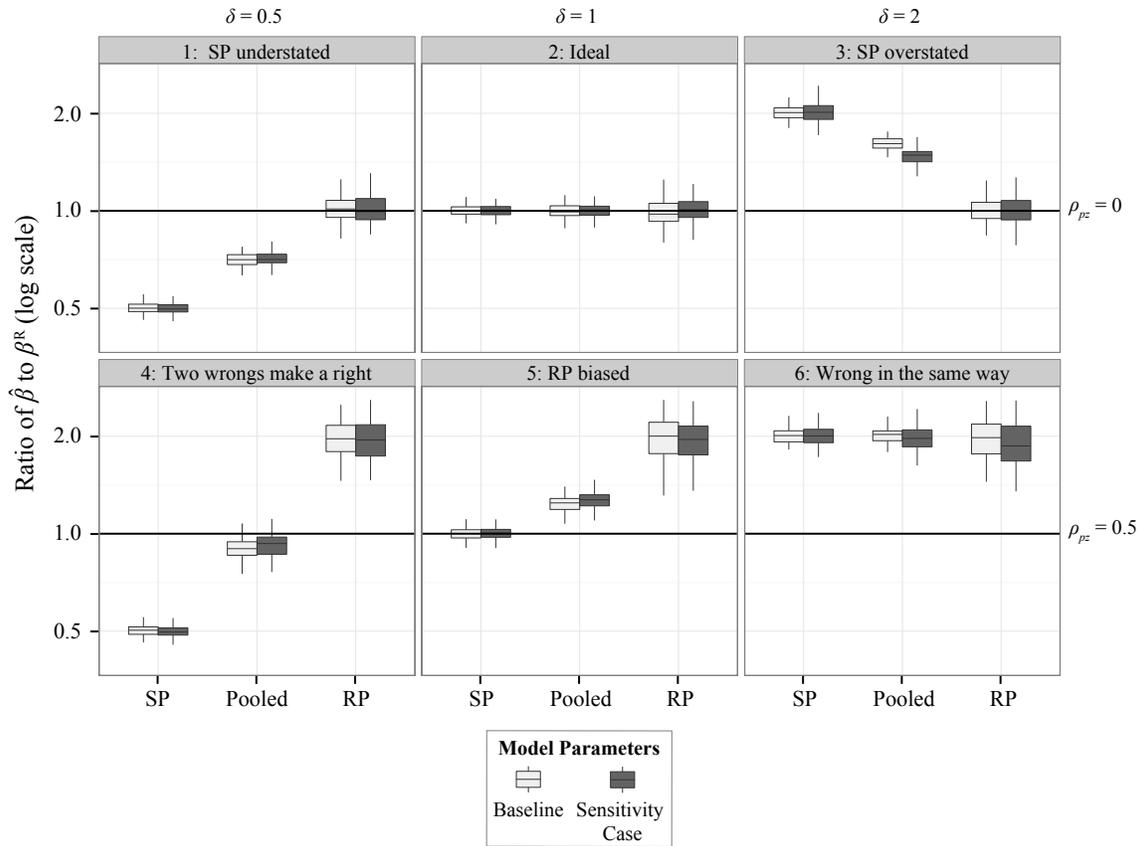


Figure B.12: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $\beta^R = 3$. Each box plot represents results from 100 simulated data sets.

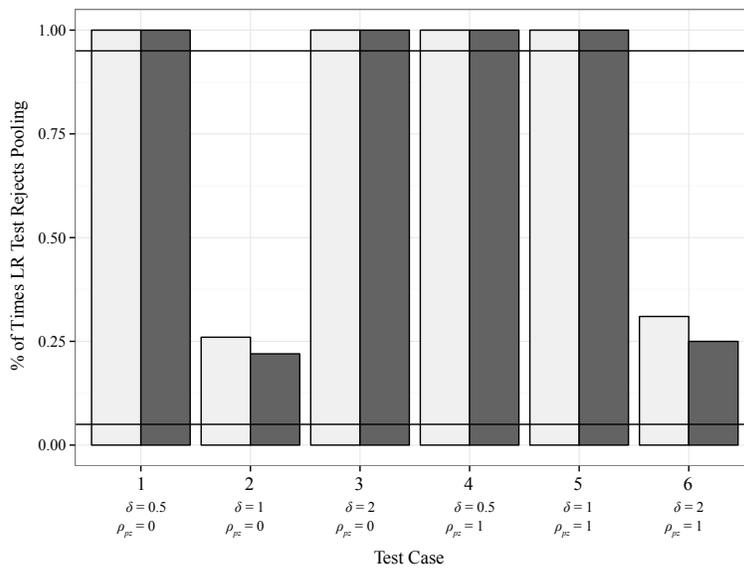


Figure B.13: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $\beta^R = 3$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

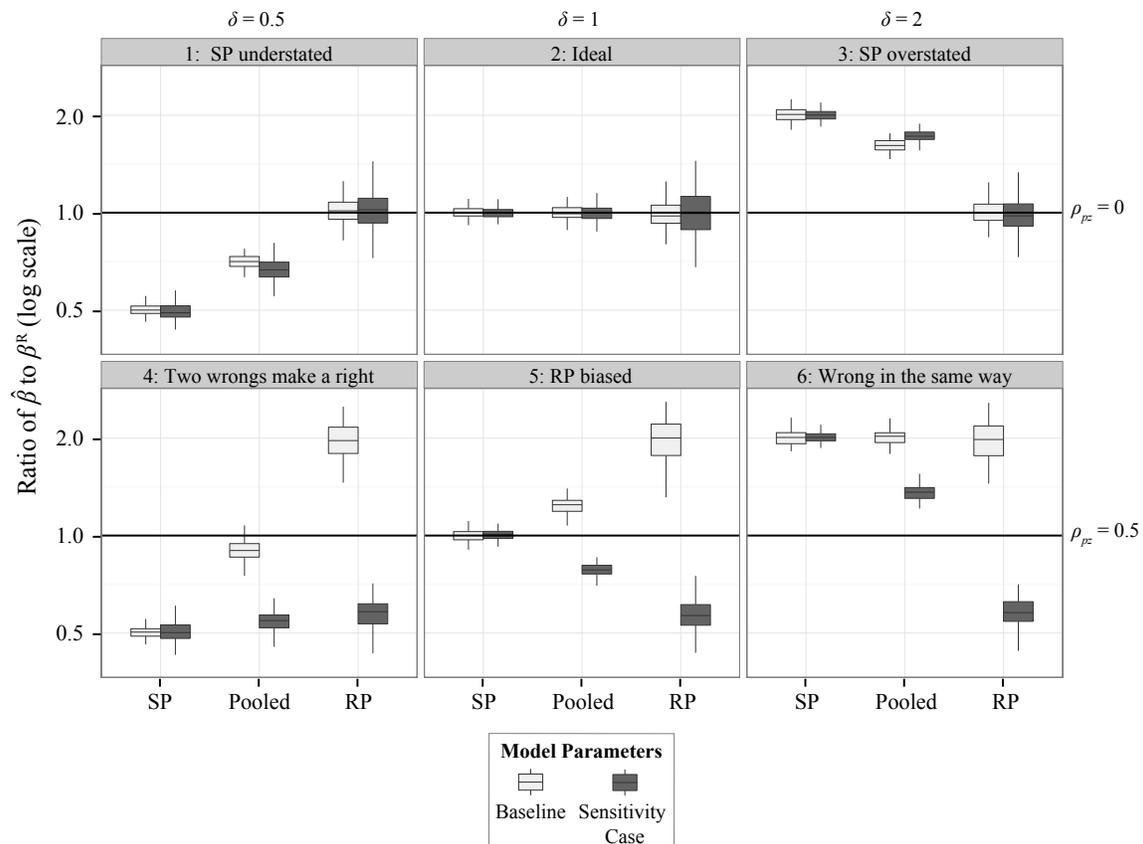


Figure B.14: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $\zeta = -1.5$. Each box plot represents results from 100 simulated data sets.

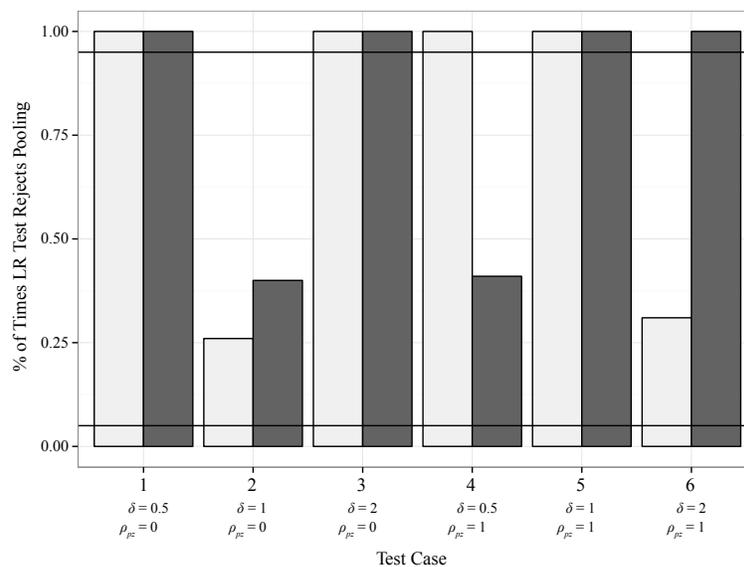


Figure B.15: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $\zeta = -1.5$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

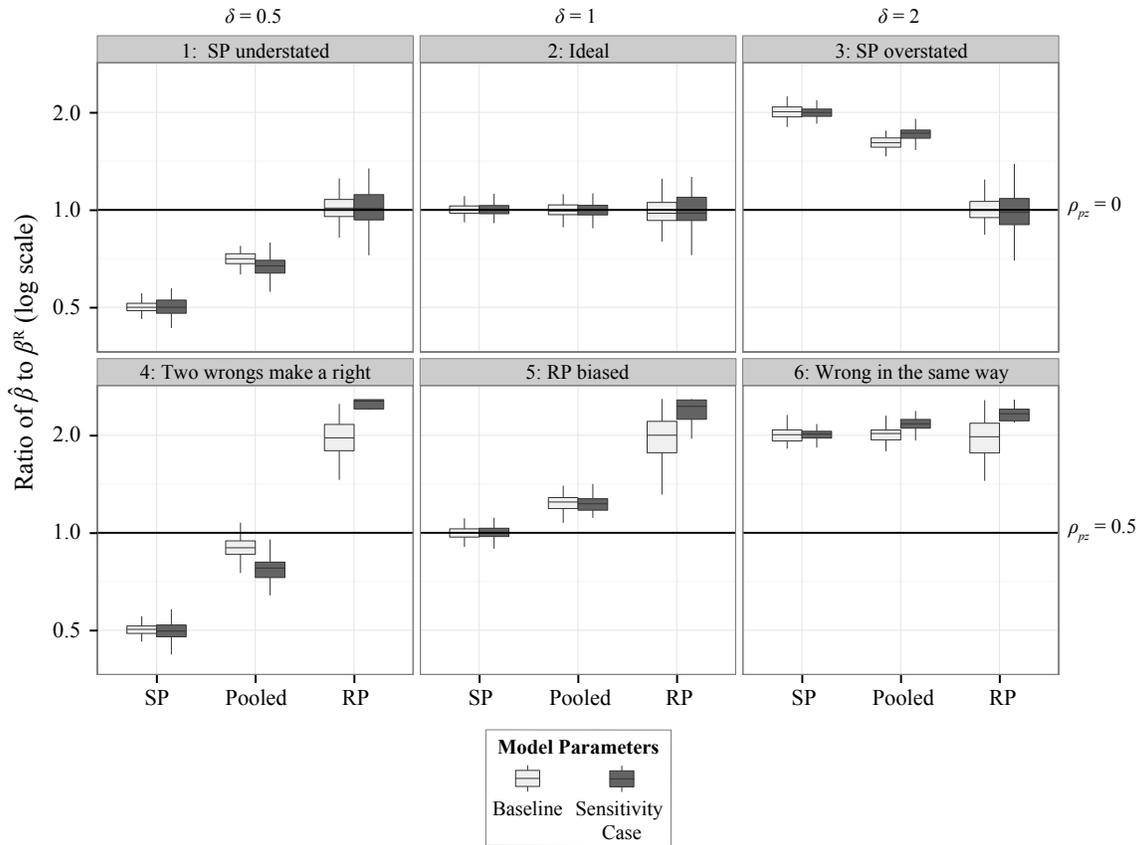


Figure B.16: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $\zeta = 1.5$. Each box plot represents results from 100 simulated data sets.

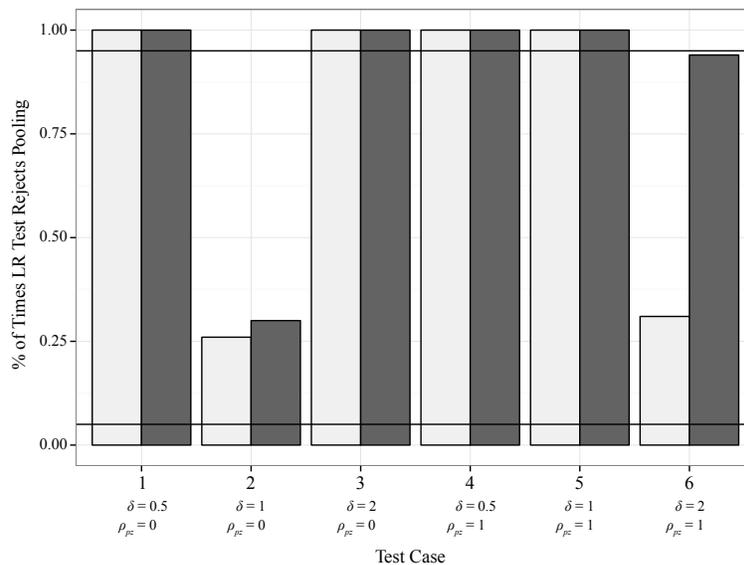


Figure B.17: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $\zeta = 1.5$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

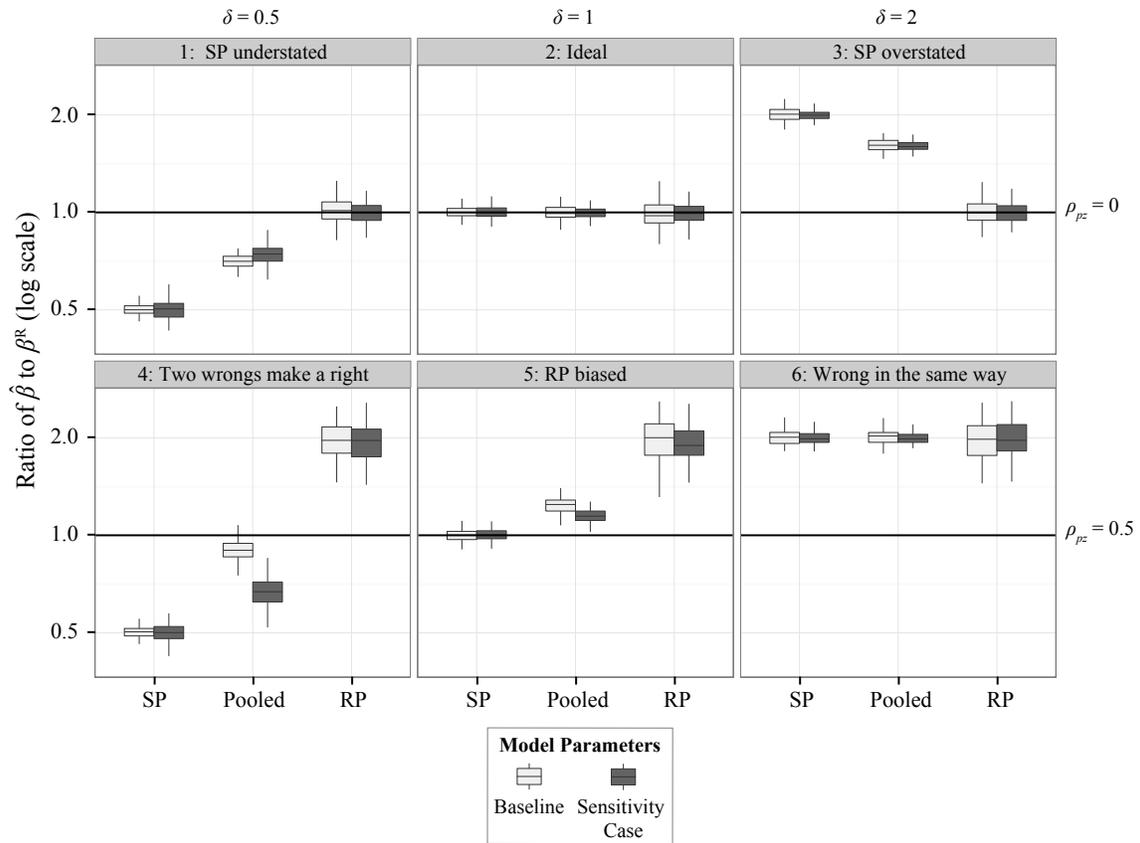


Figure B.18: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $\rho_{px} = 0.5$. Each box plot represents results from 100 simulated data sets.

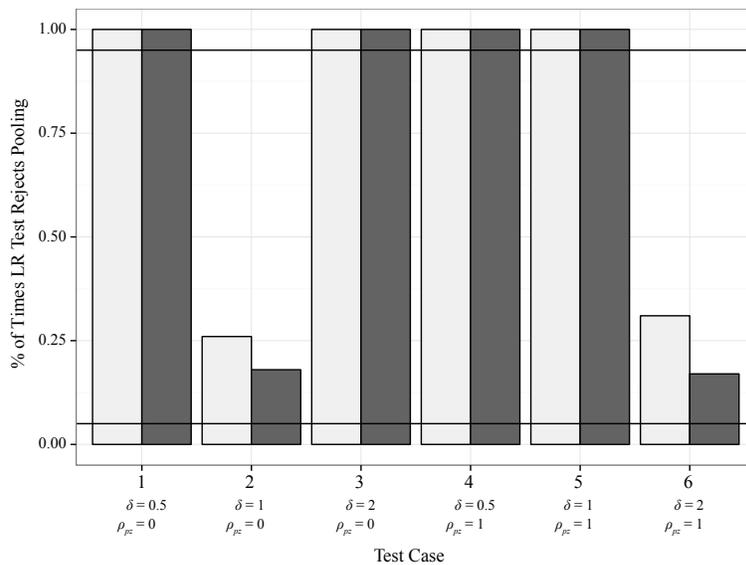


Figure B.19: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $\rho_{px} = 0.5$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

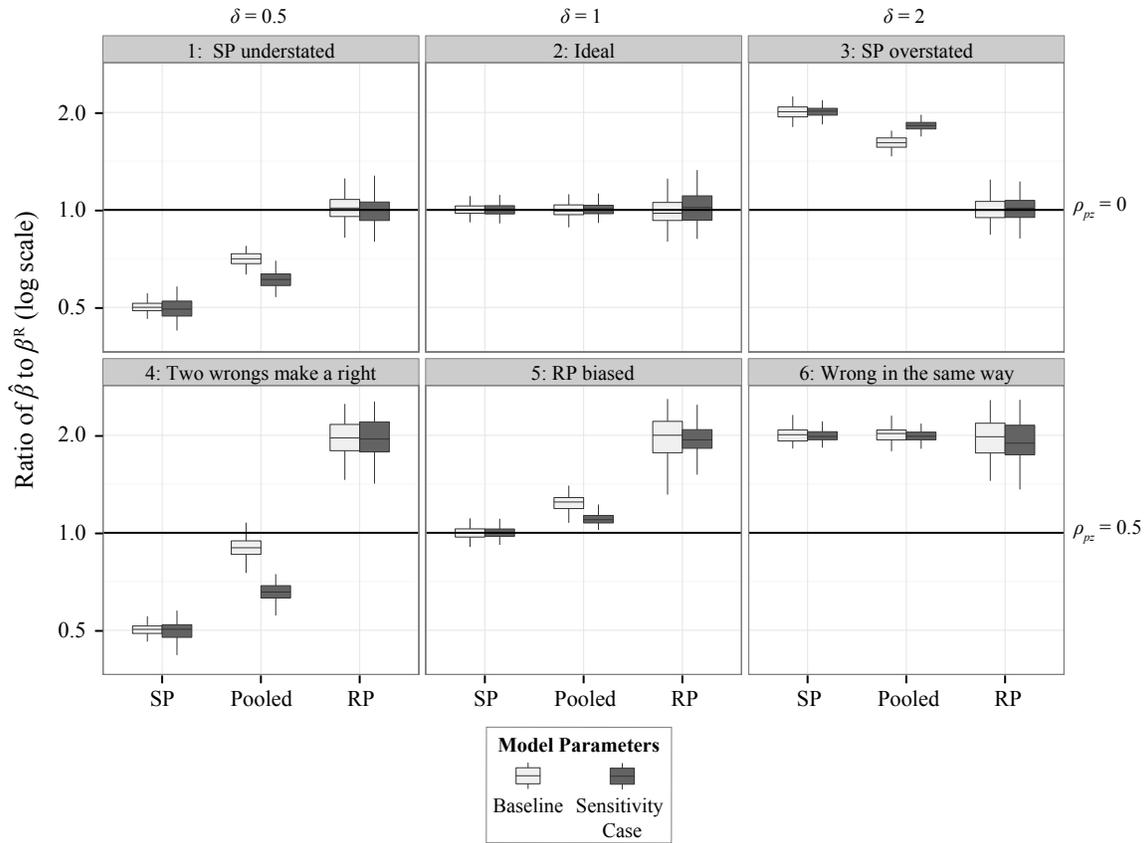


Figure B.20: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $N^R = 500$. Each box plot represents results from 100 simulated data sets.

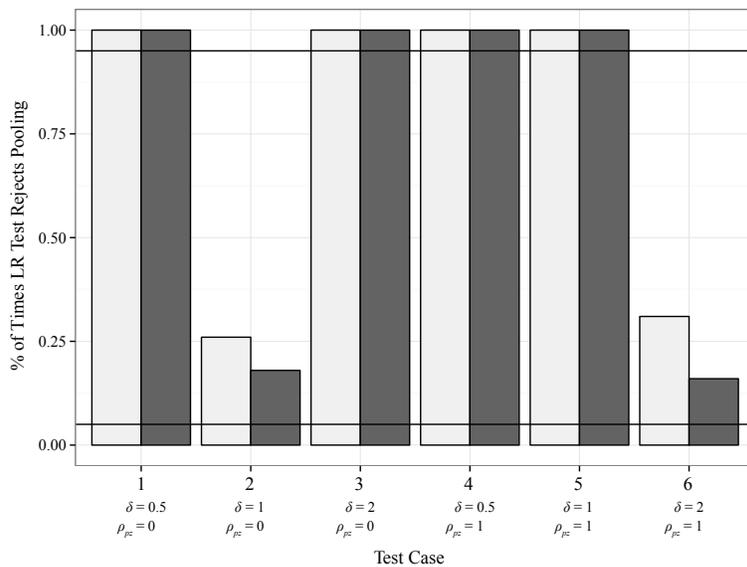


Figure B.21: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $N^R = 500$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

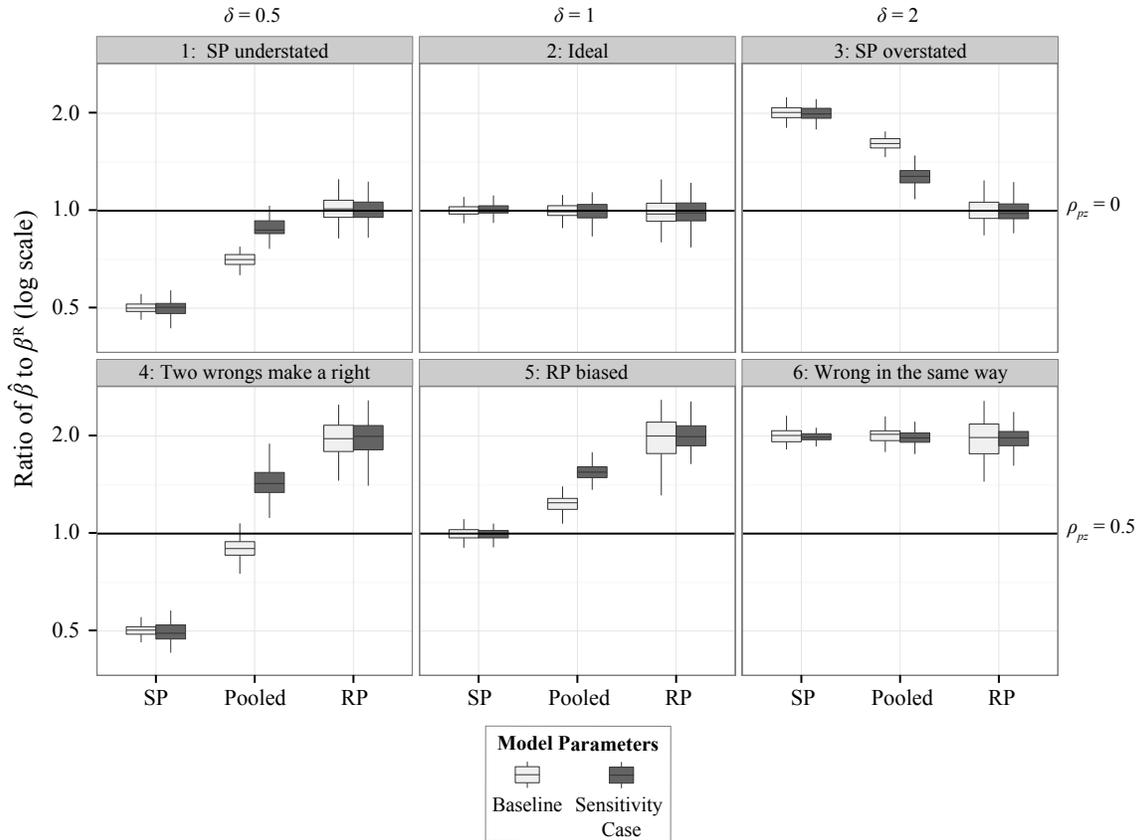


Figure B.22: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $N^R = 5000$. Each box plot represents results from 100 simulated data sets.

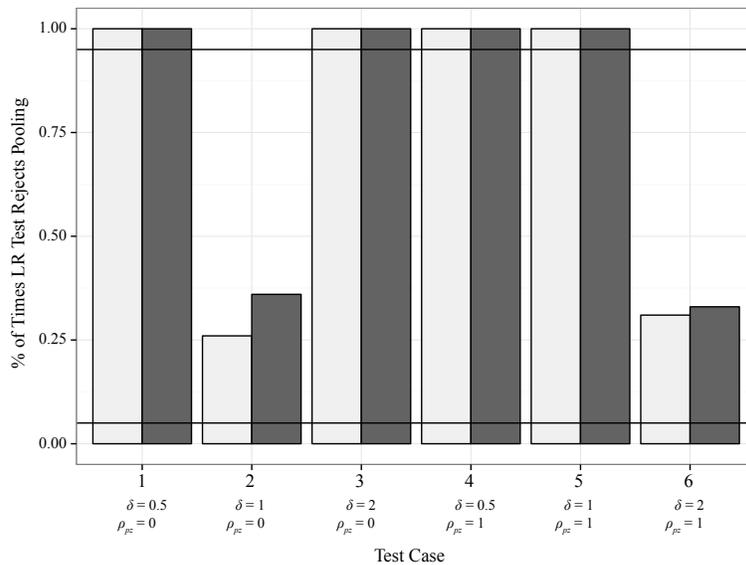


Figure B.23: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $N^R = 5000$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

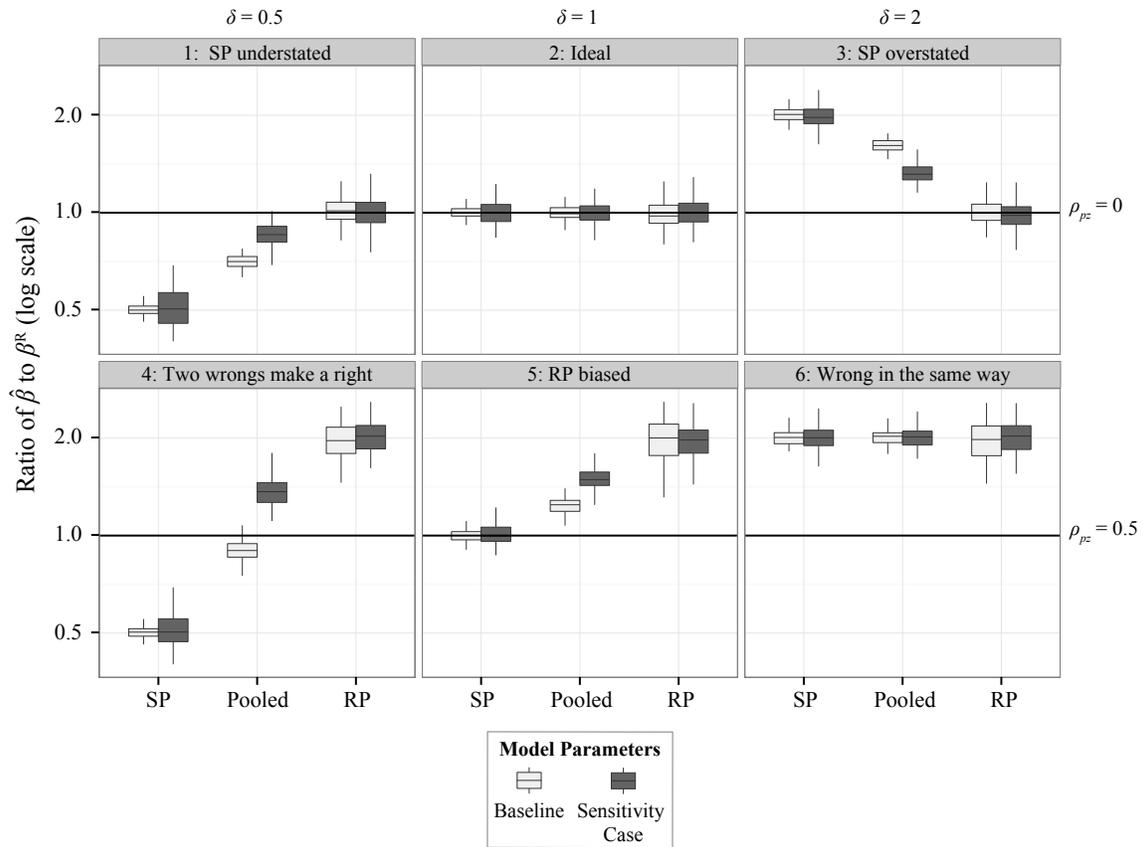


Figure B.24: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $N^S = 500$. Each box plot represents results from 100 simulated data sets.

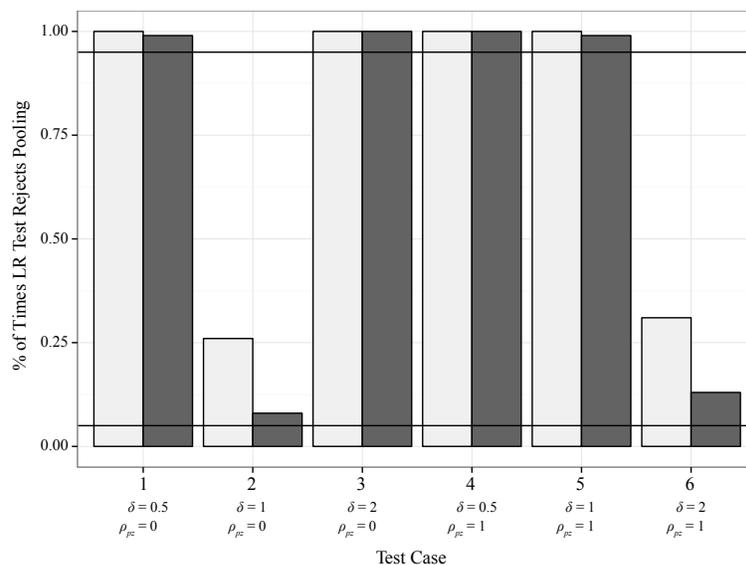


Figure B.25: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $N^S = 500$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

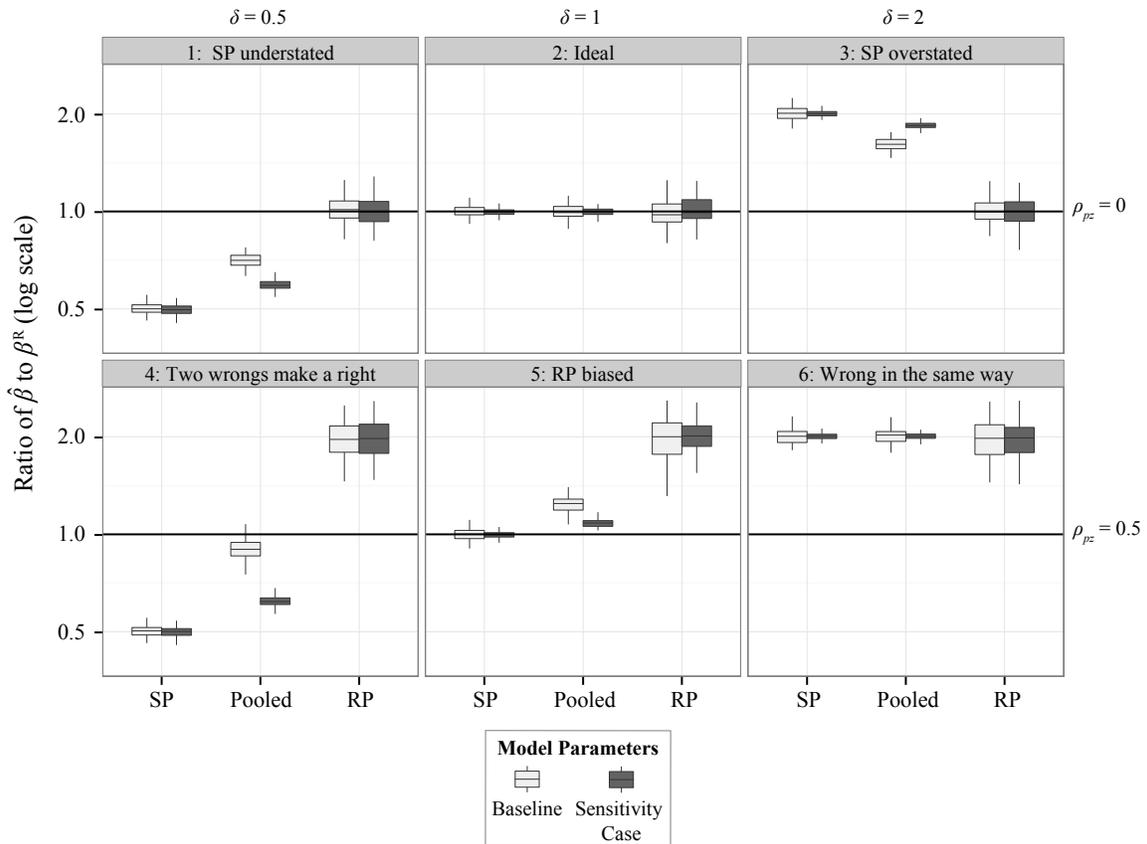


Figure B.26: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $N^S = 5000$. Each box plot represents results from 100 simulated data sets.

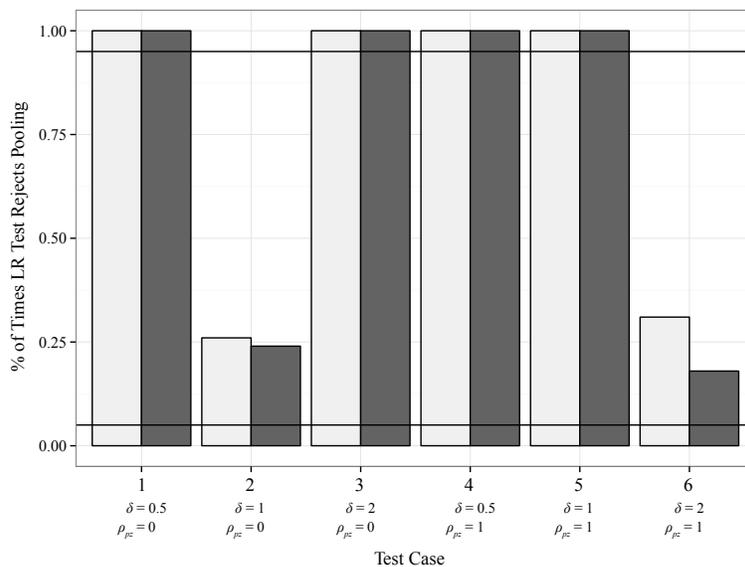


Figure B.27: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $N^S = 5000$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

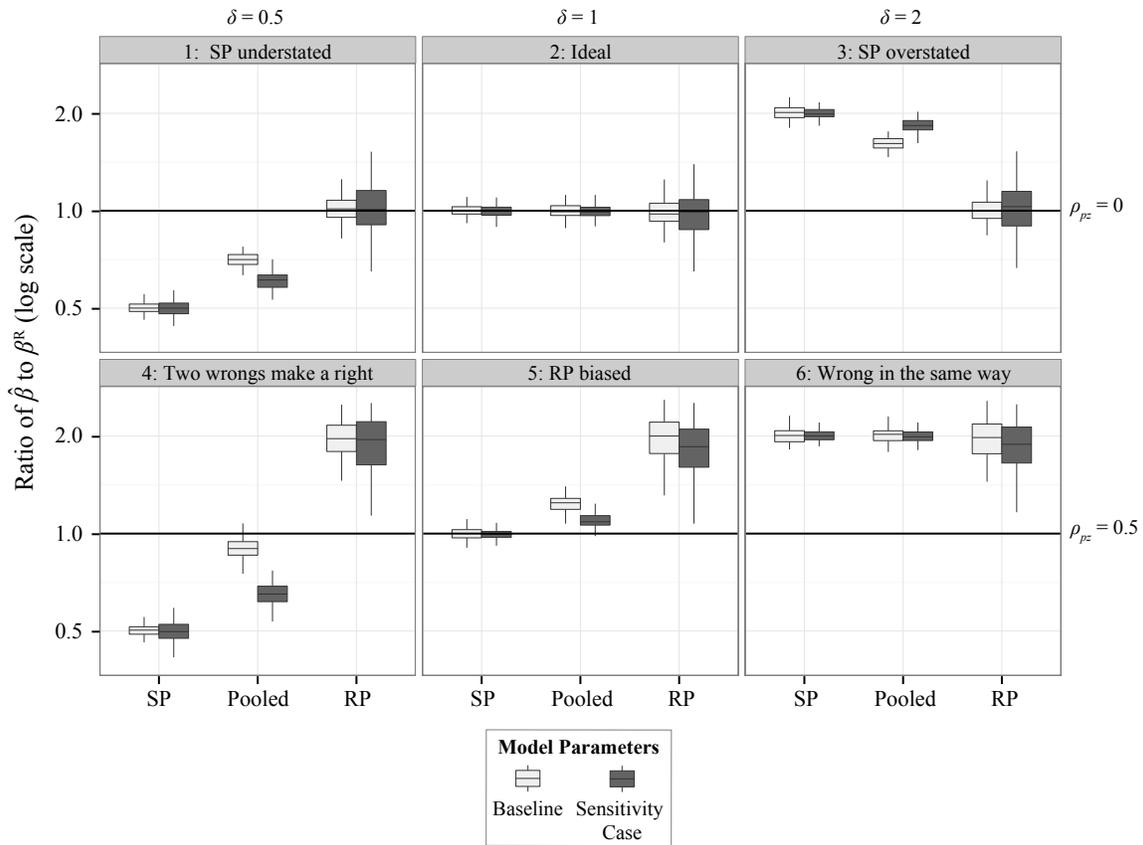


Figure B.28: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $A^R = 3$. Each box plot represents results from 100 simulated data sets.

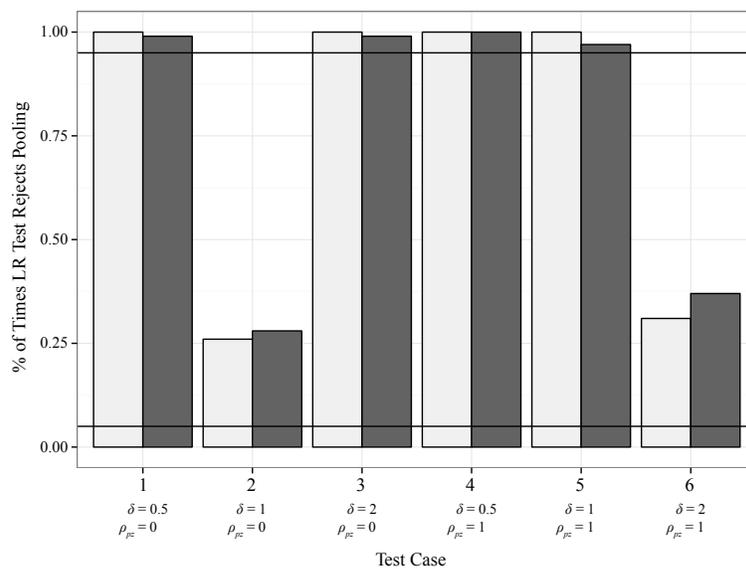


Figure B.29: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $A^R = 3$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

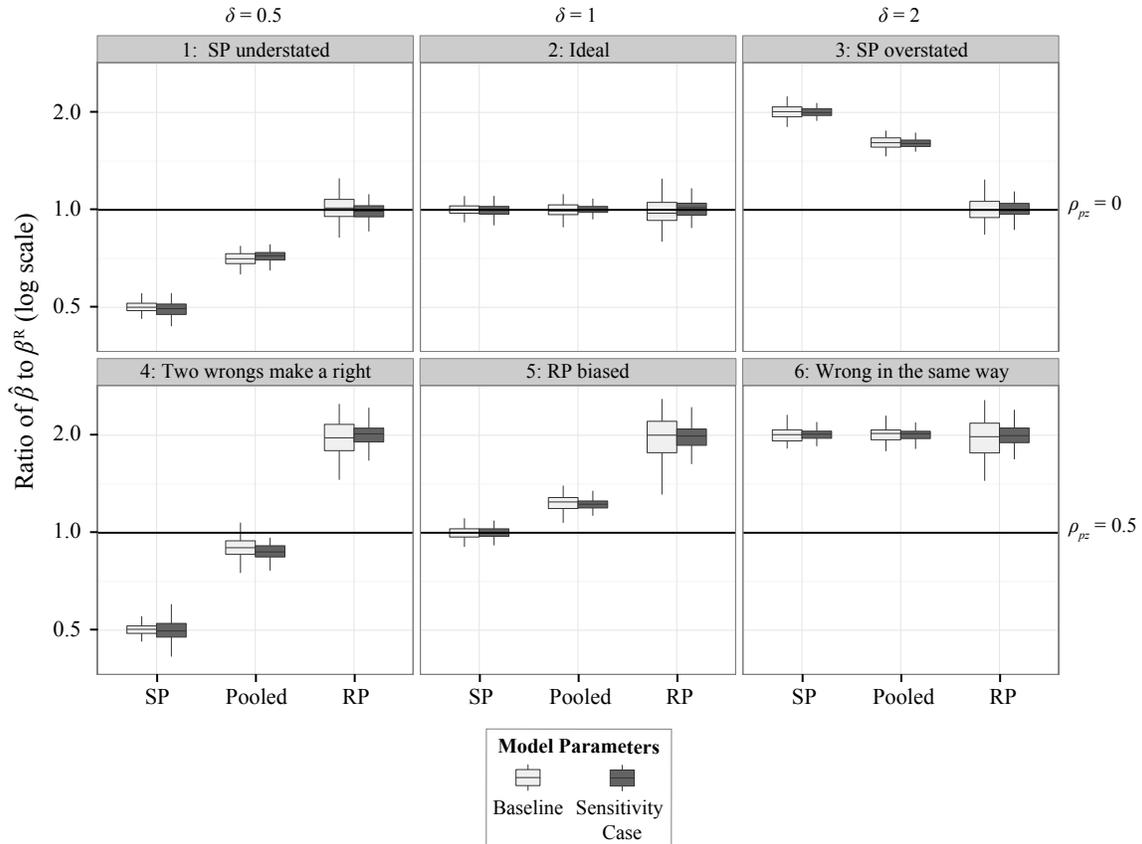


Figure B.30: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $A^R = 100$. Each box plot represents results from 100 simulated data sets.

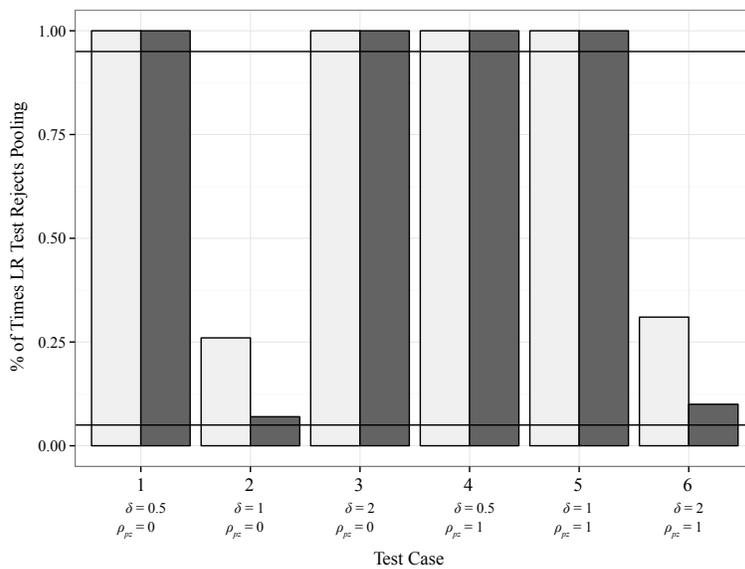


Figure B.31: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $A^R = 100$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

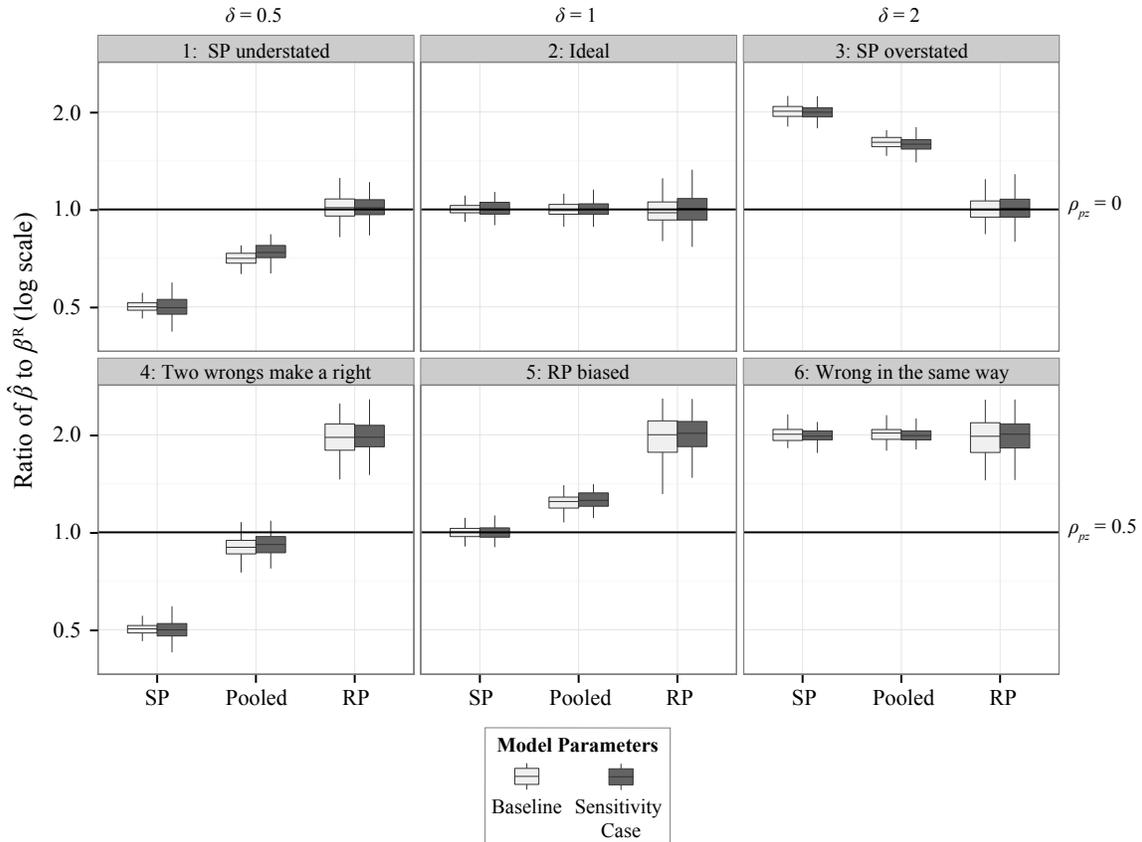


Figure B.32: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $A^S = 2$. Each box plot represents results from 100 simulated data sets.

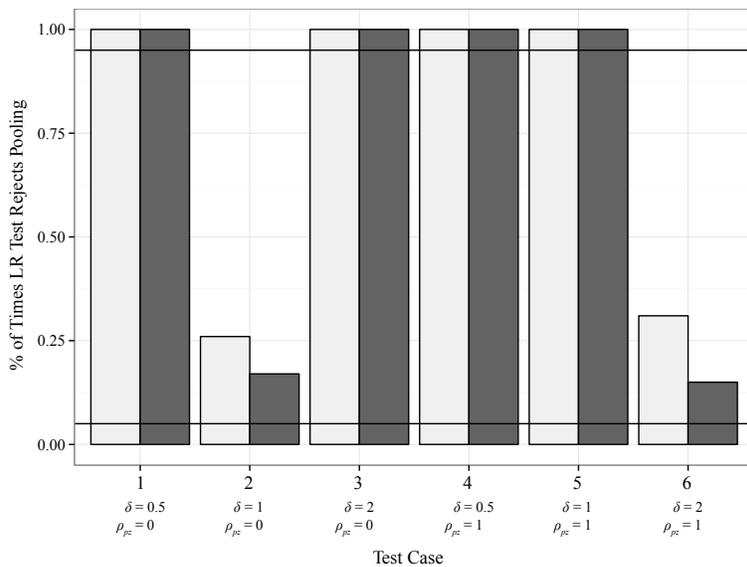


Figure B.33: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $A^S = 2$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

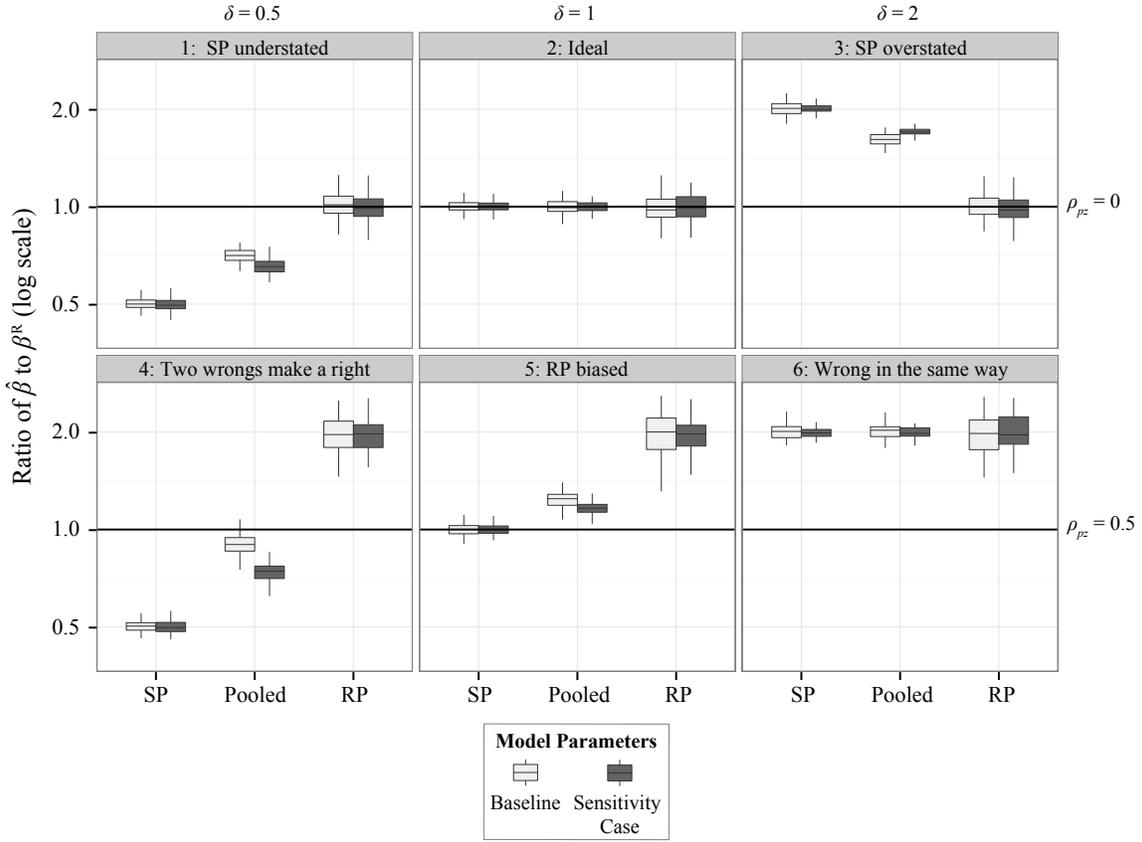


Figure B.34: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $A^S = 10$. Each box plot represents results from 100 simulated data sets.

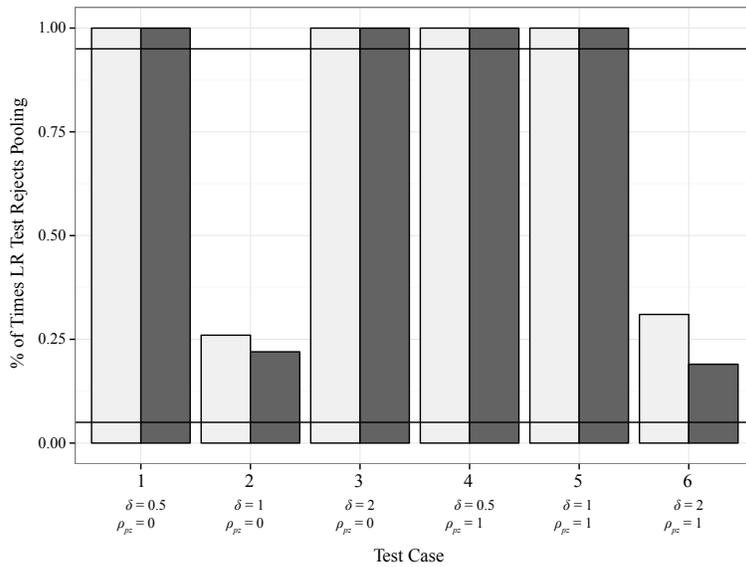


Figure B.35: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $A^S = 10$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

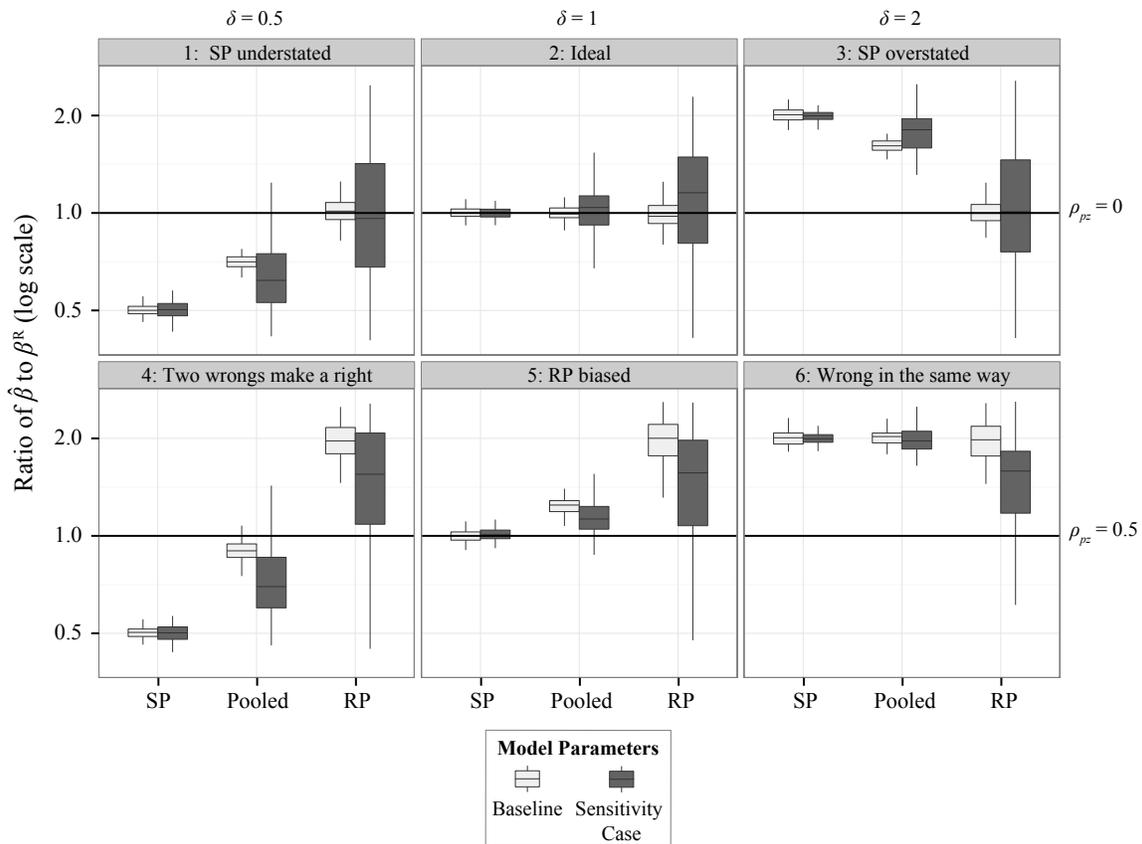


Figure B.36: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $T^R = 1$. Each box plot represents results from 100 simulated data sets.

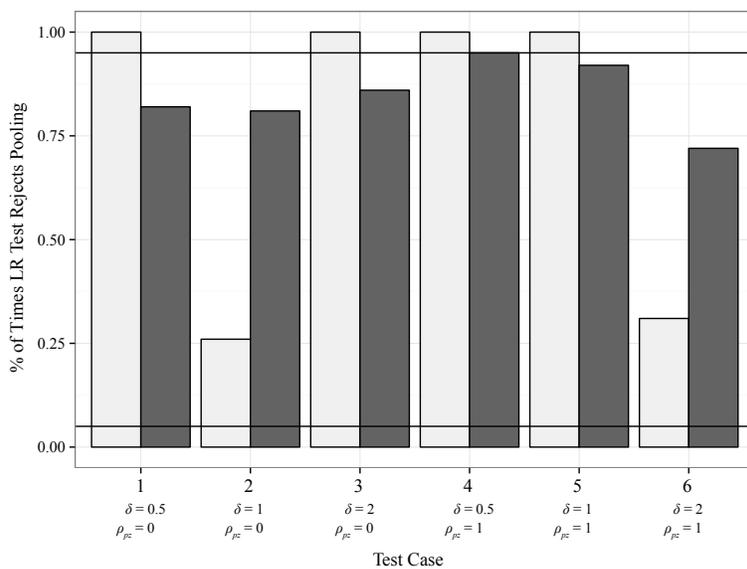


Figure B.37: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $T^R = 1$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

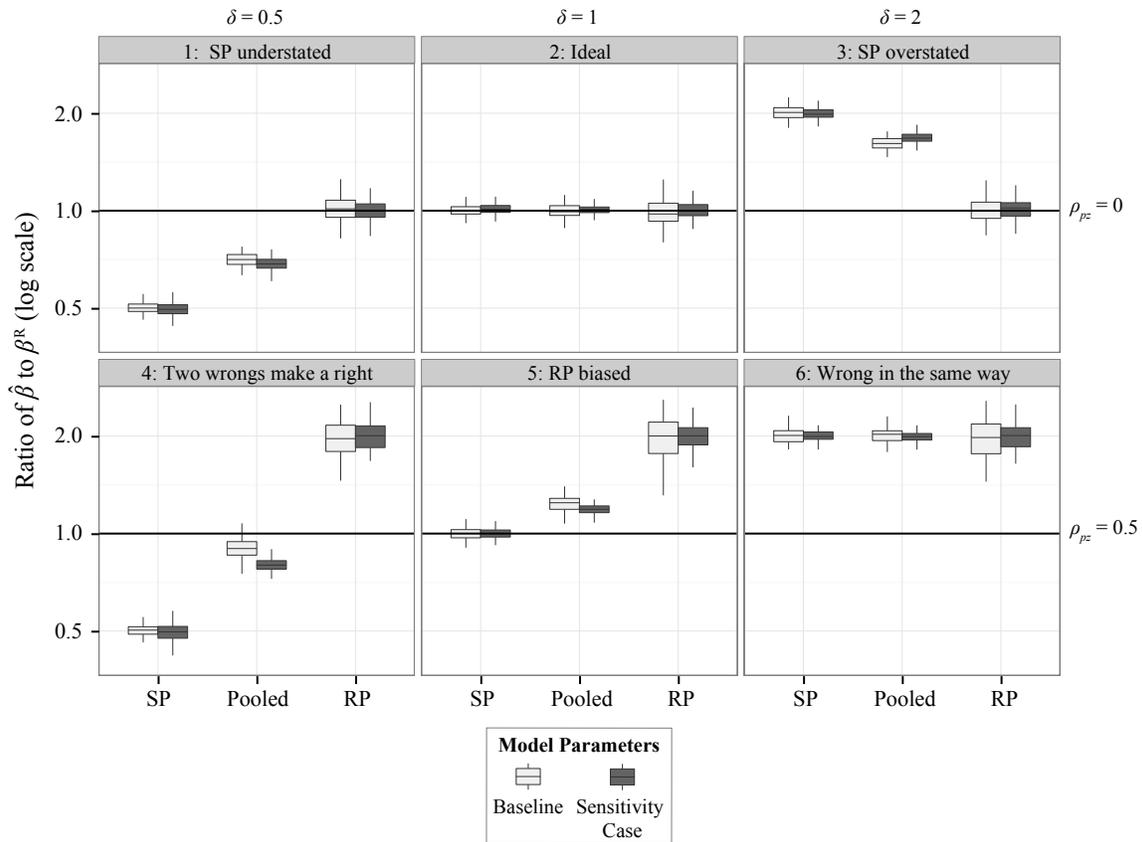


Figure B.38: SP, RP, and pooled model results of the ratio of $\hat{\beta}$ to β for the base case (light color) and sensitivity case (dark color) where $T^R = 200$. Each box plot represents results from 100 simulated data sets.

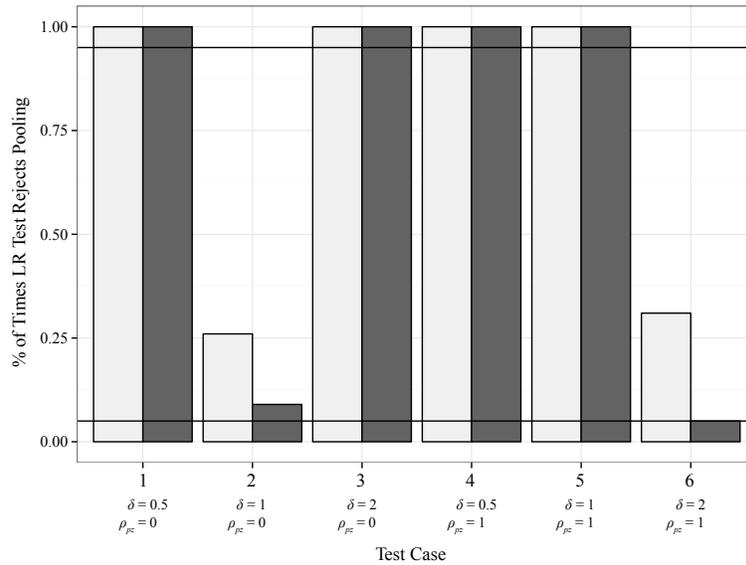


Figure B.39: Likelihood ratio rejection rate for the base case (light bars) and sensitivity case (dark bars) where $T^R = 200$. Each box plot represents results from 100 simulated data sets. Horizontal black lines indicate a 0.05 significance level.

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