PRICE ELASTICITY FOR SMARTPHONES IN THE UNITED STATES: RESULTS FROM THREE METHODOLOGICAL APPROACHES

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ABSTRACT

The Berry, Levinsohn and Pakes (BLP) model is a widely accepted model when using aggregate data to examine an industry selling differentiated products. This dissertation contributes to existing literature of the New Empirical Industrial Organization (NEIO), focusing on the BLP models and provides insights into consumer demand for smartphones by estimating two BLP models which explore own-price and cross-price elasticity of demand.

The first paper summarizes a BLP model estimated using aggregate data and compares the result to a consumer level choice model. Both models are estimated with data from the smartphone phone industry. Customer level survey data was aggregated to mimic data used when estimating a BLP model allowing for a general review for consistency between elasticity estimates. Final estimates show the BLP estimation methodology generally has higher own-price and cross-price elasticities compared with a mixed logit estimated using consumer level choice data.

The second paper included a near perfect branded complement, network connectivity, by calculating shares using smartphone, network carrier combinations and adding the carrier price. Elasticities for each smartphone dropped relative to the original smartphone only BLP.

As with many BLP models, the smartphone only and the branded complement models both suffered from poor price instrumental variables. Including the branded complement provided improved insights into the smartphone industry and allowed for more detailed cross-price elasticity calculations. BLP, in this case, can provide estimates

of own-price and cross-price elasticities for consumer noticed branded complements. This has obvious practical use as many industry participants may not have access to consumer level data of an important branded complement.

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CHAPTER I

INTRODUCTION

1.1 General Problem

For many decades economists have recognized the utility value of brand or consumer noticed product differentiation (Hunt 2011). Companies which possess differentiation power use price and non-price product characteristics to improve market position. These companies often develop products with characteristics that appeal to specific consumer segments (e.g. millennials, educated, life stage, etc.) attempting to increase overall sales and profitability. Very simply, an automobile manufacturer may paint some cars orange to appeal to one segment of the population and paint other cars gray to appeal to a different segment. These differentiation efforts complicate modeling efforts designed to understand consumer behavior in the market place.

Understanding consumer choice among differentiated products ideally would involve consumer level sales data with knowledge of basic household demographics. Personal or household specific data will often address differences in preferences for important product features.

Many times the consumer is faced with a simple choice – to buy or not to buy – rather than an overall level of consumption. For example, the purchase of a refrigerator, at any given time, may require a choice from amongst some twenty models that are fixed in design. Such a decision is markedly different than a choice such as how many potatoes to purchase. Choosing to purchase or not has a long history within the body of literature on consumer choice.

Consumer choice theory was joined with traditional consumer utility theory in the early 1970's by Dan McFadden (McFadden 1973). Applied research in consumer choice has largely depended upon the use of choice based surveys to understand consumer price, product feature and brand preference. The validity of such methods depends on the degree to which individuals respond to hypothetical scenarios in a manner which is consistent with their actual consumption behavior. In some instances, analysts have access to a population experiment or have the opportunity to conduct a product trial. However, it is often the case that none of these options are available.

When individual consumer data is unavailable, the researcher may rely on the use of aggregated data. Such data often lacks important consumer level, and otherwise observable, product information. For example, using sales summary data across time or space removes the household income linkage to a specific purchase. Furthermore, the analysis is restricted to the average price across purchases, rather than a transaction price for each individual consumption decision.

The use of aggregated data to model choice behavior within a differentiated product industry largely began in the early 1990's, but gained widespread use with the publication of "Automobile Prices in Market Equilibrium" by Berry, Levinsohn, and Pakes in 1995, commonly referred to as BLP (Berry, Levinsohn and Pakes 1995). The BLP work addresses several econometric issues which exist when using aggregate data to predict consumer choice. Over the subsequent decades, many works have adapted the BLP methodology to different industries, improved or changed estimation techniques, or revised environmental assumptions.

1.2 Specific Problem

Consumers face choices throughout each day: what to eat for breakfast, whether to take the bus or train, and which color sofa to purchase, as examples. By 2013, virtually every household in the United States also chose a cellular phone. Per the Nielsen Mobility Insights survey, nearly every household had a cellular phone during 2013 and nearly 75% of households had a smartphone.[1] Consumers face an extensive choice set of brands and models within the cellular phone market, with consumers self-reported having 453 wireless phone models in use during the narrow time horizon of third quarter 2012 to fourth quarter 2013 (Nielsen Mobility Insights Survey).

Manufacturers produce cellular phone models exhibiting many differentiation characteristics, some of which are easily observed by the consumer (e.g. screen size, weight, battery life, color, brand and warranty). Other features, such as processor speed, scratch-resistant screens, and durability, are not as obvious. Cellular phones also represent a significant budget burden to the average American household, with each phone purchase costing on average $159.86 and the average cost of smartphones being $173.95 (as of 2013). In addition, the household faces average network provider costs of $148.24 each month with a commitment to the standard contract length of approximately two years (Nielen Mobility Insights Survey 2012-2013). These costs require many households to actively align spending to accommodate the need for new phones and

[1] A smartphone is a phone using an advanced operating system, which allows users to enjoy many of the features of a personal computer (e.g. email, web browsing, games, and productivity applications).

complementary network services necessary to acquire full utility from their cellular phones.

Given the number of current cellular phone users, and the increasing number of smartphone users, an analysis of industry dynamics is warranted. An understanding of household purchases of cellular phones requires addressing price sensitivities, brand recognition, and attribute valuation. The results of which will provide insights into the behavior of the cellular phone industry.

1.3 Research Objectives

The research objective is to use traditional consumer utility theory within the context of dichotomous choice to estimate price elasticities for top smartphone models in the cellular phone industry during the period third quarter 2012 to fourth quarter 2013. More specifically, the research herein uses a large consumer level continuous tracking study of wireless phone purchases as input data to examine elasticities from a consumer level discrete choice analysis. Further, the household level self-stated response data are aggregated into defined markets, which are then used to estimate elasticities from a BLP model. The study is extended by taking advantage of a basic relationship within the smartphone industry: Each smartphone needs access to a wireless network to gain any reasonable level of utility. In this case, the consumer level tracking survey allows for the perfect, or near perfect, complement to have an identifiable brand and associated price. The complementary BLP model is estimated using industry market shares calculated across smartphone / carrier combinations. Own-price and cross-price elasticities derived

from each model are compared in order to examine possible differences, and determine if such differences are consistent with industry behavior and/or economic theory. More specifically the complementary BLP allows for investigation across both smartphone and carrier brand price differences which will help quantify impact of carrier price on smartphone sales.

1.4 Chapter Layout

This document has an overarching goal of estimating smartphone price elasticities utilizing alternative econometric methods, and then reviewing brand effects on those elasticities. Chapter II provides a literature review of cellular phone choice while chapter III reviews the smartphone market and outlines key data sources. Chapter IV summarizes a household level consumer logit model. In chapter V, data aggregated from the household level data is used to estimate a BLP model. Chapter VI extends the BLP model by defining shares-based joint consumption of the complementary products of smartphones and wireless network access. Chapter VII summarizes the key findings of this research and discusses potential extensions, including the use of other data and methodologies.

CHAPTER II

LITERATURE REVIEW OF THE CELLULAR PHONE MARKET

Mobile phones were introduced in the United States during the 1980's and established widespread use by the late 1990's. Most existing literature has focused on the features and pricing of wireless network access given the legacy of usage-based pricing. During the early period of cellular phone service, before data specific features, many network providers charged a monthly recurring charge plus a per minute conversation charge. Monthly usage billing made the wireless network providers a far more socially interesting topic than end user equipment pricing. Most studies concentrated on network monthly charges and various usage changes as the cellular industry changed over the years. For example, the industry started with per minute conversation charges, then added texting charges and data rates when technology and market conditions allowed. During this time service providers created pricing structures appealing to specific consumers, such as fixed charges for unlimited conversation minutes or and family sharing plans.

While the cellular phone was an important consumer choice, it didn't create the billing anxiety of wireless network usage charges. Thus, most studies do not consider phone models in their analysis, instead treating the phone as homogenous with varying price. Dippon (2012) used several models to estimate the impact of various charges on consumer choice of network providers. The work concluded that consumers generally consider many features when choosing a network provider. Dippon also found that consumers recognize the one time phone cost as less burdensome than the monthly

recurring charge; noting a $1 increase in phone price has less impact on provider choice than a $1 increase in the month recurring charge.

Hausman (1999), using aggregate data across 30 U.S.A. markets from 1988 to 1993 from a price elasticity of network access services to be -0.51. Ahn, Han, and Lee (2006), using data from 64 countries, found network access elasticity to be, on average, -0.36.

As the cellular phone industry matured, studies began to introduce new elements to the consumer choice analysis. Tripathi, Siddiqui and Siddiqui (2009) measured the impact of perceived network quality and perceived customers service by using conjoint analysis. Dewenter, Ralf, and Haucap (2008) used monthly wireless usage traffic data in Austria from January 1998 to March 2002 to estimate both short- and long-term price elasticities of conversation minutes. Short-term results ranged from -0.26 to -0.4 while long-term results ranged from -0.47 to -1.1.

Petruzzellis (2008) examined factors that impact phone choice in the Italian market. The work categorized cellular phones into three broad factors: utilitarian or functional uses (design, software, weight, and functions), hedonic or conspicuous consumption (brand, ability to personalize the phone, aesthetics) and economic (price, promotions). Using consumer level sample data collected from a questionnaire, the study found that while technical characteristics are important, phone brand – including past experience, some basic demographics such as income, and social dynamics – are all potential factors in phone choice.

Isaid and Faisal (2015) investigated cellular phone purchase intent in Qatar by segmenting potential explanatory variables into three defined categories: product characteristics (price, quality, size, brand), subjective norms (social influences, media), and past behavior (purchased or not). Data were collected using a questionnaire fielded to a convenience sample. Results from a regression show that while product price and features are important, both social influence and past behavior have a larger impact on cellular phone repurchase.

Li (2010) also investigated cultural, social, personal, brand and product aspects of purchasing a cellular phone in China. The study examined the repurchase of sixteen different brands using a consumer survey in May 2009. With respect to cellular phone features, overall appearance was the top factor, followed by brand and then price. The survey results show that price, like in the U.S.A., tended to remain clustered in a tight range with 65% of China cellular phone purchases buying the 100 to 200 euro range. When respondents were asked directly if cellular phone brand mattered in their repurchase, over 90% acknowledged that brand did matter in some degree. The study also collected cellular phone consumers' top information sources used to inform their purchase decisions. Sixty-eight percent of respondents gathered information from the Internet, 30% from media sources and 47% from personal recommendation. Primary reasons that started the cellular phone repurchase process were, in order of importance: current cellular phone on longer satisfied a need, new model released, out of fashion, and sales promotion.

Chen (2010) used the cellular phone market to examine product, brand and pricing as factors in both the U.S.A. and Taiwan markets. The work focused on three primary factor – product attractiveness, brand innovativeness, and price – that cue product quality and value, which then motivates cellular phone purchase intention. The results indicate that brand innovativeness does impact purchase intention.

Alshurideh et al. (2015), while examining factors that impact cellular phone brand choice, used a survey instrument that collected both cellular phone brands and network provider brands. Using a multinomial logit model, they found that behavior elements play a critical role in brand choice. More specifically, a history of positive experience with a particular brand is consistent with remaining brand inert while a negative history compels consumers to switch brands. While all consumers purchase cellular phones for utilitarian concerns like safety and convenience, consumers also consider a cellular phone purchase from the hedonic viewpoint like newest phone or social appeal.

Existing literature reflects some academic interest to understand consumer choice of a wireless network service provider, usage behavior and price sensitivity of cellular services during the early years of the industry. To date, however, few studies examine phone brand or address how specific cellular phone features impact the choice of phone model.

CHAPTER III

SMARTPHONE DATA

3.1 Defining the Smartphone for Analysis

In recent years smartphones have emerged as a common household item with 91% of American adults having a cellular phone and 56% owning a smartphone (Smth 2013). One of the classic problems facing any researcher when analyzing a market that doesn't have obvious product or brand categories is how to organize and create defined products for analysis. The smartphone industry is a perfect example of this issue. First, as a result of the research objective, the Nielsen Mobility Insights survey was used for analysis. The Nielsen source data is a continuous cellular phone tracking survey that, during the period of analysis(third quarter of 2012 to fourth quarter of 2013), found respondents self-reporting 453 different cellular phones using at least 20 different network carriers through-out the U.S.A. The Nielsen Mobility Insights survey collected phone make and model, price, and basic demographics from 263,355 respondents during the period of analysis, averaging over 40,000 completed interviews each quarter. This large sample allows for the potential to aggregate data across selected metropolitan areas for the BLP estimation. Many of the 453 cellular phones were easily dismissed as non-smartphone by missing attributes such as Internet access, not having an email application or not having a web browser application. Eventually 242 phones were investigated to obtain specifications likely important to a consumer. Final attributes used for analysis were talk time, screen size, weight and price. Talk time, screen size, and weight are reported by manufacturers and price was determined using the respondent reported

Nielsen phone price. Eventually, smartphones that use iOS, Android, Windows, or the Blackberry operating system having a screen size equal to or larger than 3.5 inches, introduced after 1/1/2010, and having a market share of 1% or greater, were included for analysis. The 1% share criteria was a response to calculating reasonably reliable mean smartphone prices from the Nielsen Mobility Insights data.

3.2 Smartphone Data Sources

Empirical data comes from the Nielsen Mobility Insights survey. Each quarter Nielsen collects approximately 90,000 interviews from wireless customers. Sample is acquired from various online panels designed to represent the entire U.S.A. This study uses data collected during third quarter of 2012 to fourth quarter of 2013 for respondents 18 years and older that currently have a smartphone. The Nielsen sampling methodology is stratified across 102 metropolitan areas plus all other locations. To insure adequate sample, metros with 1500 or more sample observations are used for analysis. Sample by the 30 selected metros is summarized in Table 3.1. Data includes a metropolitan area indicator, smart phone model coded into key attribute dummy variables, brand dummy variables, and smartphone price. The Nielsen interview also collects basic demographic data: income, gender, age, race, number living in the household, and number of children. All observations are respondent stated.

Table 3.1 Sample Observations by Metro and Quarter

Metro	Q4 2012	Q1 2013	Q2 2013	Q3 2013	Q4 2013	Total
New York, Northern New Jersey, Long Is.	720	820	1368	988	641	5201
Los Angeles, Riverside, Orange County	727	809	1371	980	585	5134
Dallas, Fort Worth	516	659	794	833	541	3755
San Francisco, San Jose, Oakland	508	651	874	753	469	3690
Chicago, Gary, Kenosha	478	563	824	687	480	3442
Houston, Galveston, Brazoria	456	523	737	767	493	3325
Miami, Fort Lauderdale	409	538	695	678	476	3138
Washington, D.C. excluding Baltimore	403	521	604	608	414	2867
Philadelphia, Wilmington, Atlantic City	411	462	573	609	386	2793
Atlanta	379	442	626	564	343	2664
Boston, Worcester, Lawrence, Lowell, Brockton	379	449	449	518	320	2422
Detroit, Ann Arbor, Flint	358	429	518	539	292	2404
Phoenix, Mesa	367	458	423	471	347	2340
San Antonio	312	396	480	522	344	2293
Denver, Boulder, Greeley	332	422	430	518	328	2275
San Diego	307	373	487	505	329	2258
Sacramento, Yolo	285	378	444	438	304	2047
Las Vegas	270	339	388	469	305	1962
Orlando	253	346	410	447	283	1948
Kansas City	260	307	361	417	283	1841
Baltimore	261	298	349	424	277	1829
Minneapolis, St Paul	298	359	337	360	268	1825
Seattle, Tacoma, Bremerton	270	340	356	373	225	1771
Columbus	261	301	328	392	273	1752
Portland, Salem	259	301	321	388	254	1741
St Louis	283	304	288	388	261	1740
Tampa, St Petersburg, Clearwater	283	300	312	394	238	1729
Charlotte, Gastonia, Rock Hill	221	292	308	418	237	1648
Indianapolis	240	287	301	356	257	1608
Pittsburgh	260	280	282	353	207	1570

Source: Nielsen Mobility Insights Survey, 2013

Within the Nielsen Mobility Insights survey methodology participants self-report their current phone by responding to a series of questions that leads to a phone selection from graphical illustrations. Selected product specifications for each self-reported

smartphone model were collected from manufacture documentation. These following characteristics were coded for analysis: OS type (Android, iOS, Windows and Blackberry), screen size, weight, and battery life measured in talk time. The Nielsen survey collected price using the question: "How much did you actually pay for your current cell phone ***after*** any trade-ins and/or rebates were subtracted from the list/retail price?" This question should lead to good pricing variation as smartphone sellers regularly offer promotions, rebates, and other discounting. Table 3.2 illustrates, at a national level, the overall market share, pricing, and basic features for these twenty five devices in the selected 30 metros. Each smartphone has features (talk time, weight and screen size) which are observed by both consumers and econometrician. This features represent the x_{jt} within the BLP model and will be used as product specific exogenous variables in the mixed logit. Screen size is measured in diagonal inches, weight in grams, and talk time in hours. Note phone average age calculated as the difference between the interview month and phone introduction date is also reported in Table 3.2.

Table 3.2 Device Share, Average Price and Features, 2013

Device	Share	Price	Age	Screen Size	Weight	Talk Time
Apple iPhone 4S	15.90%	$184.51	20.72	3.5	140	8
Apple iPhone 4	13.40%	$130.76	36.36	3.5	137	7
Apple IPhone 5	12.60%	$228.92	9.92	4	112	8
Samsung Galaxy S III	10.60%	$174.03	14.18	4.8	133	22
Samsung Galaxy S II	3.00%	$177.19	26.56	4.3	116	18
Samsung Galaxy S4	2.70%	$223.80	5.38	4.99	130	14
Samsung Galaxy Note II	1.90%	$253.01	9.12	5.55	180	35
Apple iPhone 5S	1.20%	$239.30	0.06	4	112	10
Motorola Droid RAZR	1.10%	$133.79	19.28	4.3	127	12
HTC Evo 4G	1.10%	$139.96	35.15	4.3	170	6
Motorola Droid RAZR M	1.00%	$80.81	9.79	4.3	126	20
LG Motion Optimus Regard	0.90%	$121.14	10.74	3.5	132	5
Motorola Droid RAZR MAXX	0.80%	$171.05	8.79	4.7	157	32
Samsung Galaxy Nexus	0.70%	$140.29	18.96	4.65	135	8
Samsung Galaxy S Blaze 4G	0.60%	$164.10	14.87	3.97	128	7
HTC Evo 4G LTE	0.60%	$145.80	13.61	4.7	134	12
HTC One	0.60%	$203.11	5.34	4.7	143	19
Samsung Galaxy S 4G	0.60%	$171.75	35.37	4	119	13
Samsung Galaxy Exhibit 4G	0.60%	$171.37	19.95	3.7	116	5
Samsung Stratosphere	0.50%	$81.01	20.03	4	164	8
HTC Inspire 4G	0.50%	$81.14	27.34	4.3	164	6
Samsung Admire / Vitality	0.50%	$100.65	21.12	3.5	117	3
Motorola Droid Bionic	0.50%	$135.75	21.07	4.3	159	10
LG Lucid / Optimus Exceed	0.50%	$57.14	14.21	4	142	8
Motorola Droid X	0.50%	$112.51	35.28	4.3	155	8

Source: Nielsen Mobility Insight Survey, 2013

Further descriptive data illustrating cellular phone price variation in the Neilson Mobility Insights survey are noted in Table 3.3. Most new phone models start with a high price and are then discounted each quarter as they age and new models are introduced to the market. Note the Samsung Galaxy S4 was on the market in the first quarter, Y13Q3. The Apple iPhone models illustrate how newer phone models force

discounting of older versions. During the second quarter of 2013 the newest Apple model, iPhone 5, cost $238 while the maturing iPhone 4S costs $195 and the iPhone 4, set to be phased out had average cost of $136. Notice that several phones were introduced during 2013: The Samsung Galaxy S4 and HTC One in the market during the first quarter, while the Apple iPhone 5 entered during the third quarter of 2013.

Table 3.3 Device Average Prices and Price Standard Deviation, 2013

Phone	Y13Q1	Y13Q2	Y13Q3	Y13Q4	Avg.	Std. Dev.
Apple iPhone 4S	$200.14	$195.73	$180.17	$164.73	$184.51	$16.11
Apple iPhone 4	$150.21	$136.80	$121.67	$112.39	$130.76	$16.67
Apple IPhone 5	$230.06	$238.57	$227.73	$219.21	$228.92	$7.96
Samsung Galaxy S III	$183.15	$185.37	$167.18	$166.07	$174.03	$10.23
Samsung Galaxy S II	$195.99	$167.04	$170.48	$183.96	$177.19	$13.27
Samsung Galaxy S4	N/A	$241.44	$219.20	$223.63	$223.80	$11.77
Samsung Galaxy Note II	$228.63	$252.24	$250.40	$285.99	$253.01	$23.68
Apple iPhone 5S	N/A	N/A	N/A	$239.30	$239.30	N/A
Motorola Droid RAZR	$144.44	$140.34	$126.78	$121.14	$133.79	$11.01
HTC Evo 4G	$138.18	$149.79	$131.50	$135.71	$139.96	$7.83
Motorola Droid RAZR M	$96.97	$82.77	$71.12	$76.55	$80.81	$11.15
LG Optimus Regard	$123.87	$115.38	$114.25	$132.78	$121.14	$8.62
Motorola Droid RAZR MAXX	$172.63	$177.49	$177.37	$157.97	$171.05	$9.21
Samsung Galaxy Nexus	$150.49	$146.00	$136.82	$119.58	$140.29	$13.67
Samsung Galaxy S Blaze 4G	$186.52	$136.84	$148.67	$201.77	$164.10	$30.70
HTC Evo 4G LTE	$163.65	$156.66	$134.79	$130.54	$145.80	$16.22
HTC One	N/A	$224.23	$203.15	$198.70	$203.11	$13.63
Samsung Galaxy S 4G	$145.81	$155.42	$190.87	$239.77	$171.75	$42.54
Samsung Galaxy Exhibit 4G	$159.48	$168.09	$181.35	$182.03	$171.37	$10.92
Samsung Stratosphere	$70.30	$85.80	$85.09	$85.58	$81.01	$7.60
HTC Inspire 4G	$77.38	$77.54	$81.01	$100.40	$81.14	$11.01
Samsung Admire / Vitality	$109.72	$97.48	$97.94	$97.70	$100.65	$6.01
Motorola Droid Bionic	$144.33	$136.17	$132.31	$128.22	$135.75	$6.87
LG Lucid / Optimus Exceed	$62.15	$51.10	$60.71	$55.24	$57.14	$5.09
Motorola Droid X	$123.41	$93.65	$118.31	$110.73	$112.51	$13.01

Source: Nielsen Mobility Insight Survey, 2013

In addition to phone model and price information, each smartphone model uses basic demographic data for estimation. The consumer level choice model summarized in chapter IV uses household level consumer attributes directly associated to smartphone choice, while models summarized in chapters V and VI use metropolitan specific random draws of household characteristics during estimation. Two specific demographic questions – income and number of children in the household – are pulled from the Nielsen sample. Both income and children have shown good explanatory power over a wide number of household choice models (Dippon 2012). Income represents potential to purchase and the presence of children in the household is associated with a potential budget stress or, possibly, a motivation to purchase some products. The specific questions and response categories are noted in Figure 3.1.

Which of the following income categories best describes your total [INSERT PREVIOUS YEAR] household income before taxes?

01 Less than $15,000
02 $15,000 to $24,999
03 $25,000 to $34,999
04 $35,000 to $49,999
05 $50,000 to $74,999
06 $75,000 to $99,999
07 $100,000 to $124,999
08 $125,000 to $149,999
09 $150,000 to $199,999
10 $200,000 to $249,999
11 $250,000 or more
99 Decline to answer

How many children in each of the following age categories currently live in your household? If you do not have any children in a particular age category, please leave blank.

6 0 - 4 years old
7 5 - 9 years old
8 10 - 12 years old
4 13 – 15 years old
5 16 – 17 years old

Please enter your age. *Please enter a whole number.*

Figure 3.1 Select Nielsen Demographic Questions

Source: Nielsen Mobility Insights Survey, 2013

Using the smartphone definition discussed in section 3.1 and Nielsen respondents age 18 and over, within the selected 30 metros, the respondent level sample equals 63,883 observations facing 1,291,189 cases for the consumer specific estimation.

CHAPTER IV

SMARTPHONE CHOICE USING CONSUMER LEVEL DATA

4.1 Discrete Choice Theory and Mixed Logit Models

Contemporary companies recognize the value of product differentiation, and most consider finding both product and brand separation from competitors to be necessary for financial success in retail industries (Kotler 2000). In recent decades, companies have found several new media sources which advantage those able to differentiate product or brand. Tracking internet browsing behavior, online purchase habits (Kelly, Gayle and Drennan 2010); (McMahan, Hovland and McMillan 2009), cellular phone usage, cellular phone advertising (Choi, Hwang and McMillan 2008), social media activity (K. L. Keller 2009) and interactive digital TV (Bellman, Schweda and Varan 2012) all create incentives to provide new brands and features which appeal to specific consumer interests.

Since the McFadden (1973) paper, discrete choice models have been an ever growing methodology to understand choice behavior in the context of consumer utility theory. McFadden's original work assumed independence of irrelevant alternatives (IIA). The IIA restriction considers the switching behavior of consumers to be independent of other product characteristics. Simply, an Apple iPhone 5 price change is assumed to have equal impact on consumers of the iPhone 4 and Samsung Galaxy SIII switching to the Apple iPhone 5. In many cases the IIA restriction doesn't address the market reality. Take the specific smartphone example noted above: one would expect feature differences

like operating system or screen size to create an asymmetric migration to the Apple iPhone 5.

A mixed logit was estimated using the consumer level data which provides relief from IIA and provides a test for price heterogeneity which may lead to consumer specific elasticity estimates. Mixed logit can also rely on the McFadden conditional logit specification to avoid estimating a voluminous number of price coefficients within a choice set. Conditional logit models are derived under an assumption that the decision maker engages in utility-maximizing behavior, and are part of the class of random utility models (RUM). The RUM, as best illustrated in McFadden (1973), requires a decomposition of the utility function:

$$u_{ij} = Z_j\gamma + \varepsilon_{ij} \tag{4.1}$$

where utility u_{ij} for consumer i consuming product j has a predictable element $Z_j\gamma$ and a random element ε_{ij}. McFadden first defines a model which includes product characteristics specific to a choice alternative. Let $Z_j$represent the characteristics of alternative j and γ measures the effect of product specifics on choice. When using consumer level data, household characteristics may be added as noted in equation 4.2

$$u_{ij} = Z_{ij}\gamma + X_i\beta + \varepsilon_{ij} \tag{4.2}$$

where X_i are consumer specific demographics, β measures the effect of consumer specifics on choice. The errors, ε_{ij}, are assumed to be iid extreme value leading to the logit estimation:

$$p_{jt}\left(Z_{ij,}\,\gamma,\, X_i, \beta\right) = \frac{exp\left(Z_{ij}\gamma + X_i\beta\right)}{\sum_{j=1}^{J}\exp\left(Z_{ij}\gamma + X_i\beta\right)} \tag{4.3}$$

As noted in McFadden (1973) and Train (2003) this specification leads to alternative independent probability ratios and restricted substitution patterns.

Mixed logit resolves IIA issues by allowing consumer tastes to be unique within the utility model, which leads to less restrictive substitution given that the probabilities ratios between two products are a function of attributes from other alternatives. Starting with the standard utility function 4.1, the mixed logit specification allows parameters $\gamma_i$and β_i to change by consumer i.

$$U_{ij} = Z_{ij}\gamma_i + X_i\beta_i + \varepsilon_{ij} \tag{4.4}$$

Both $\gamma_i$and $\beta_i$vary by observation and, for the purposes of this research, have a normal distribution characterized by the form $\beta_i = \beta + \sigma_\beta$ and $\gamma_i = \gamma + \sigma_\gamma$ where β and γ are now mean values with normal variance. To simplify notation let β represent both β_i and γ_i, and θ the mean and variance of β. Probabilities are calculated using:

$$P_{ij} = \int L_{ij}(\beta) f(\beta|\theta) d\beta \tag{4.5}$$

where

$$L_{ij}(\beta) = \frac{e^{\beta' X_{ij}}}{\sum_{j-1}^{J} e^{\beta' X_{ij}}} \tag{4.6}$$

This specification now requires simulation to obtain estimates for β. Equation 4.7 and 4.8 illustrate a process which uses repeated random draws from a population each used to minimize a log-likelihood function.

$$\widetilde{P_{ij}} = \frac{1}{R}\sum_{r=1}^{R} L_{ij}(\beta^r) \tag{4.7}$$

R is the number of draws from a population or sample. The simulated probabilities are then inserted into a log-likelihood function to provide a simulated likelihood.

$$LL = \sum_{j=1}^{J} \sum_{i=1}^{I} d_{ji} ln\widetilde{P_{ij}} \tag{4.8}$$

where $d_{ji} = 1$ represents the case in which consumer i chose product j, zero otherwise. The estimator searches for values of θ minimizing the log-likelihood function 4.7.

Elasticity estimates from random coefficient logit aren't calculated using substitution patterns restricted by IIA (Train, 2003). The elasticity equation 4.9 uses information from alternatives other than choices j and k. The percentage change in the probability for one alternative is now subject to a change in other attributes, m, and $\beta^m$is the mth element of β.

$$E_{\mathrm{ik}x_{ij}^m} = -\frac{1}{P_{ik}} \int \beta^m L_{ik}(\beta) L_{ij}(\beta)\, f(\beta) d\beta \tag{4.9}$$

$$= -\int \beta^m L_{ij}(\beta) \left(\frac{L_{ik}(\beta)}{P_{ik}} \right) f(\beta) d\beta$$

Each elasticity is uniquely calculated across all choices j and k. Calculations specific to this paper use equations 4.10, and 4.11 (Greene and Hensher 2010):

$$E_{jk} = \frac{1}{N} \sum_{i=1}^{N} \int_{\beta_i} \left[\delta_{jk} - P_k(\beta_i, x_i) \right] \beta_m x_{mki} d\beta_i \tag{4.10}$$

$$E_{jk} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{R} \sum_{r=1}^{R} \left[\delta_{jk} - P_k(\beta_{ir}, x_i) \right] \beta_{mir} x_{mki} \tag{4.11}$$

4.2 Mixed Logit Data Preparation

The Nielsen Mobility Insights survey instrument did not include a product choice design as seen with most mixed logit stated preference data. The questionnaire only collected the current self-stated smartphone choice for each respondent. To construct the mixed logit choice set, all phone choices within a given time period were found and used as the likely choice set for each respondent in that time period. Suppose respondent, "*i*", chose the iPhone 4S in time "*t*". In time period "*t*", respondent "*i*" was exposed to N_t phone alternatives, where the uncollected alternatives are$(N_t - C_{it})$. C_{it} is equal to the chosen phone by respondent "*i*" in time period *t*, an iPhone 4S (Ben-Akiva and Gershenfeld 1998). For *t*=Y12Q3 the distribution of all phones chosen is represented in Table 4.1.

Table 4.1 Smart Phone Counts

Smart Phones	Count
Other Phone	2,445
Apple iPhone 4S	1,400
Apple iPhone 4	1,649
Samsung Galaxy S III	239
Samsung Galaxy S II	190
Motorola Droid RAZR	146
HTC Evo 4G	253
Motorola Droid RAZR MAXX	85
Samsung Galaxy Nexus	84
Samsung Galaxy S Blaze 4G	51
HTC Evo 4G LTE	43
Samsung Galaxy S 4G	88
Samsung Exhibit II 4G / Galaxy Exhibit 4G	60
Samsung Stratosphere	72
HTC Inspire 4G	136
Motorola Droid Bionic	93
LG Lucid / Optimus Exceed	25
Motorola Droid X	137

Source: Nielsen Mobility Insights Survey, 2013

The distribution in Table 4.1 represents 18 different smartphones, N_t, chosen by respondents in Y12Q3. For respondent *"i"* who chose the iPhone 4S, a random draw from the Y12Q3 set of the remaining $(18 - 1) = 17$ smartphones populates price for other smartphone alternatives. The remaining 17 smartphone alternatives for respondent "*i*" are data which are not made available by the survey instrument. Each of the 17 missing smartphone prices for respondent "*i*" are randomly drawn from the distribution of other like smartphones chosen by other respondents during Y12Q3. For the alternative iPhone 4, which was not chosen by respondent "*i*" in quarter Y12Q3, a random draw

from the 1,649 observed iPhone 4 prices chosen by other respondents during Q12Q3 was used to populate the unrecorded iPhone 4 price for respondent "*i*" in time Y12Q3.

Data used for the mixed logit included 63,883 respondents facing 1,291,189 choices. Only respondents with a non-missing age, income, household size and marital status responses were included for analysis. These same 63,883 observations will also be used to create aggregate data used for BLP model estimation outlined in chapters V and VI.

4.3 Consumer Level Mixed Logit Results

The mixed logit includes the same phone features eventually used to estimate the BLP model; specifically price, screen size, talk time, and weight. Two interaction variables introduce some chooser specific demographic variation, (McFadden and Train 2000). Each phone feature enters the model with assumed normally distributed random coefficients while the interaction variables enter the estimation with fixed coefficients. All four random coefficient mean values and the two interaction coefficients are statistically different from zero at $\alpha = 0.05$. Only screen size was statistically significant among the four random coefficient standard deviations estimates.

Table 4.2 Estimated Coefficients and t-values

Parameters	Estimate	Standard Error	t-values
Phone Price (Mean)	-0.000956	0.0000891	-10.72
Phone Price (Std. Dev.)	-0.000001793	0.001499	-0.00
Screen Size (Mean)	-1.5933	0.0156	-101.87
Screen Size (Std. Dev.)	1.5280	0.0231	66.07
Talk Time (Mean)	0.006405	0.002082	3.08
Talk Time (Std. Dev.)	0.0000497	0.0195	0.00
Phone Weight (Mean)	-0.003303	0.000318	-10.38
Phone Weight (Std. Dev.)	0.0000097023	0.006434	0.00
Phone Price * Income	0.000253	0.0000153	16.49
Talk Time * Household Size	0.001328	0.000596	2.23

Log Likelihood = -179,709
The mixed coefficients were estimated using 100 draws.
Optimization Method: Dual Quasi-Newton

The smartphone price coefficient is negative and statistically significant, while the corresponding smartphone price estimated standard deviation is statistically no different than zero. This result suggests that individual households make similar purchase decisions in response to smartphone price levels. Fewer respondents gravitate to larger screens, but each respondent may have unobserved unique reasons to choose a phone that has a larger screen, given screen size has a statistically significant standard deviation coefficient to screen size. In fact, the mean and standard deviation coefficients for screen size are absolutely close in size, 1.59 and 1.53 respectively suggesting other unobserved factors impact screener size choice or that screen size is a highly variable smartphone attribute. As expected, smartphone choice improves with longer talk times. The interaction with smartphone talk time and households suggests that large households, possibly with more children, are likely to purchase longer talk time phones. The talk

time standard deviation coefficient is not statistically significant, meaning talk time length impacts household smartphone choice about the same across the population of smartphone users.

Own-price elasticities of six smartphone models were calculated and illustrated in Table 4.3. These six smartphone models, having the highest market shares during the research time horizon, were also considered close substitutes within the higher priced smartphone segment. The calculated mixed logit own price elasticities of demand are inelastic for each smartphone model. Results show the two newest smartphones, the Apple iPhone 5 introduced in September of 2012 and Samsung Galaxy IV inducted in April 2013, were also highest price, and had the highest price elasticities of demand. As smartphones age and prices drop, so does the price elasticity of demand. The iPhone 4S, introduced in October 2011, has a lower price elasticity of demand than the iPhone 5, but higher elasticity than the iPhone 4, which was introduced in June 2010. The Apple iPhone models have slightly lower price elasticity of demand within the same "newest" time periods.

Table 4.3 Own Price Elasticity – Mixed Logit

iPhone 5	-0.1992
iPhone 4s	-0.1488
iPhone 4	-0.1081
Samsung S IV	-0.2026
Samsung S III	-0.1540
Samsung S II	-0.1476

Cross-price elasticities of demand for three smartphone models are illustrated in Table 4.4. Cross-price elasticities show the iPhone 4S and iPhone 4 as closer substitutes

compared to the Samsung S III. The two iPhone models are arguably quite similar so they should be close substitutes for consumers. It may also suggest that consumers generally stay within a specific smartphone brand portfolio. Elasticities derived from the mixed logit suggest the Samsung S III is not highly substitutable with either of the iPhone models, with cross-price elasticities of approximately 0.004.

Table 4.4 Cross-price Elasticity Comparison

RC-Logit	iPhone 4S	Samsung S III
Samsung S III	0.004	
iPhone 4	0.017	0.004

Beyond brand and phone aesthetics, each brand has a unique attribute in the operating system that is utilized. Apple has a proprietary operating system on each of the iPhone models and all of the Samsung Galaxy model II, III and IV are equipped with Android. While it's beyond the scope of this work to understand what compels a person to choose one operating system over another, it is likely that when a consumer uses one operating system for some period of time, the learning process necessary to switch generates inert behavior and thus reduces cross-price elasticities of demand between Apple and Samsung Galaxy smartphone models (Peng and Wang 2006) (Colgate, et al. 2007).

CHAPTER V

AGGREGATE DATA BASED CHOICE MODEL

While sampling unchosen smartphone prices to populate uncollected data allowed a mixed logit to be estimated, it introduced measurement error for each respondent. Aggregating the data for estimation within a BLP framework provides a possible solution while maintaining relief from IIA. BLP estimation using aggregated consumer choice data can provide estimates and corresponding elasticities.

Recall that the survey instrument used to collect consumer level data did not expose participants to smartphone choice. The survey collected a respondent's self-stated phone choice and the self-reported price for the chosen smartphone. A choice set was constructed for analysis using random prices from other respondents in a like time period. The random assignment of prices for all unchosen smartphones for a respondent likely created a price set different from the price set the consumer was exposed to during the actual choice event. In fact, no one should expect a respondent to recall a historical purchase in such detail that they are able to recall both the unchosen smartphone models and corresponding prices. A BLP model allows for consumer level choice using data aggregated by market and estimated under the accepted economic utility theory.

This chapter provides a basic review of the historical foundation of BLP estimation. Section 5.1 reviews choice and shares estimation before and after the foundation BLP paper, Berry, Levinsohn, and Pakes (1995). It starts with the 1973 McFadden conditional logit model then summarizes earlies BLP estimation and outlines several extending papers up to 2014. Section 5.2 outlines a classic BLP methodology

used to estimate aggregated data in the smartphone industry derived from consumer specific data which was collected in the Nielsen Mobility Insights survey. Section 5.3 reviews data specifics important to BLP estimates of a smartphone model, and section 5.4 summarizes both the BLP model coefficients and derived own-price and cross-price elasticities.

5.1 BLP Historical Review

Understanding consumer choice among differentiated products ideally would involve consumer level sales data with knowledge of basic household demographics. In many cases, especially when data are aggregated, modelers lose important consumer level and otherwise observable product information. For example, using sales summary data across time or space removes the household income linkage to a specific purchase. Further, modelers must use average price rather than a specific transaction price. Using aggregated data to model choice behavior within a differentiated product industry creates two econometric issues. First, hard to observe variables at the aggregate level such as quality, reputation, and consumption experience collect in the error term. Second, these unobserved or unmeasured variables may be correlated with price, causing parameter estimation bias (Berry, Levinsohn, and Pakes 1995). The Berry, Levinsohn and Pakes (1995) work addressed several consumer theory and estimation issues when using aggregated data to estimate price elasticities of heterogeneous products.

The Berry, Levinsohn and Pakes (BLP) model continues to be a widely accepted aggregate data methodology to examine an industry selling differentiated products. The

BLP model improves on earlier work by (Lancaster 1971) and (McFadden 1973) which solved degrees of freedom, or dimensionality, problems when using limited observations by using product attributes rather than a large number of substitute prices to calculate elasticities. McFadden's conditional logit model, as with other logit specifications, suffers from independence from irrelevant alternatives (IIA), which restricts elasticity calculations (Train 2003). Random coefficient logit, or in this case BLP, allows like products to be more substitutable than those with different features or pricing. Further, Lancaster's Hedonic model and McFadden's original conditional logit model didn't allow for, or estimate, the impact unobservable product characteristics have on choice (Ackerberg, et al. 2005). The BLP model establishes a method that collects all unobserved product features into one variable used to help explain consumer choice.

Beyond the original 1995 BLP work came many papers analyzing other industries, reviewing properties of the BLP method, and adding new independent or instrumental variables. Helpful industry specific papers include (Chu 2010), (Chidmi and Lopez 2007), (Knittel and Metaxoglou 2012), (Goeree 2008), and (Copeland 2014). (Chu 2010) considered several market outcomes as a new firm enters a differentiated market. Most assume a new entrant would, all else equal, lower price and/or increase service quality. But firms in a differentiated market with product quality flexibility may choose another path, one of lower price and lower product quality. These outcomes are certainly within the choice set of the smartphone industry.

(Chidmi and Lopez 2007) examined elasticities across two differentiated brands, a breakfast cereal product set and grocery stores. Results illustrated how breakfast cereal

prices and store brands can be associated within the BLP framework. This work captured the effects of differentiated complementary brands without a pricing measurement for grocery stores.

(Knittel and Metaxoglou 2012) developed several models to review the stability of BLP estimation by using two well-known data series (automobiles and breakfast cereal). He found using different optimization algorithms, convergence tolerances, and starting values greatly impacted results and elasticity calculations. The Knittel paper provides empirical suggestions to consider when estimating a BLP model.

(Goeree 2008) used the BLP model and aggregate advertising data demonstrated the importance of product information in a changing market place. His work finds that models are biased, typically too elastic, without product information or advertising, and that aggregate level advertising data will improve elasticity estimates. This paper shaped each section of our work, adding both advertising and social media data to each model.

(Copeland 2014) examines how consumers use intertemporal substitution rather than brand substitution within a given automobile model year to capture late year model rebates. This type of substitution is likely to occur within the smartphone data. Waiting for the new phone and subsequent old model price discounts is a well-known behavior among consumers and smartphone sellers. Both the (Goeree 2008) and (Copeland 2014) works provided exceptional insights for this paper.

5.2 Smartphone BLP Estimation Methodology

The initial work by (S. T. Berry 1994) along with (Nevo 2000) explain nicely the theoretical foundation and estimation methodology necessary to analyze an industry using a BLP model. Starting with a utility function excluding a consumer specific income component:

$$u_{ijt} = x_{jt}\beta_i - \alpha_i p_{jt} + \xi_{jt} + \varepsilon_{ijt} \tag{5.1}$$

where u_{ijt} is the utility of consumer i, for product j in market t. x_{jt} are product characteristics observed by the analyst, p_{jt} is the price of product j in market t, ξ_{jt} represents the unobserved to the analyst product j characteristics in market t. α_i and β_i are consumer specific parameters to estimate. This leaves the logistic error ε_{ijt} which adds unique value to each utility function. α_i and β_i are consumer specific utility values often decomposed using (S. T. Berry 1994):

$$\begin{bmatrix}\alpha_i \\ \beta_i\end{bmatrix} = \begin{bmatrix}\alpha \\ \beta\end{bmatrix} + \Pi D_i + \Sigma v_i \, , D_i \sim P_D\,(D), v_i \sim P_v\,(v). \tag{5.2}$$

In the above, α and β are constants, or means, across all customers. D_i are observable customer characteristics and v_i are unobserved consumer specific characteristics. P_D and P_v are distribution functions for both the observable, D_i, and unobservable, v_i, customer characteristics. P_D is a known distribution. Π and Σ are fixed parameters linking customer characteristics to the consumer specific parameters in equation 5.1. The estimation of α and β allow u_{ijt} to be decomposed into mean and consumer specific utilities per Berry, 1994.

$$u_{ijt} = \delta_{jt}\left(x_{jt}, p_{jt}, \xi_{jt}; \theta_1\right) + \mu_{ijt}\left(x_{jt}, p_{jt}, D_i, v_i; \theta_2\right) + \varepsilon_{ijt} \tag{5.3}$$

$$\delta_{jt} = x_{jt}\beta - \alpha p_{jt} + \xi_{jt}$$

$$\mu_{ijt} = \left[p_{jt}, x_{jt} \right]' (\Pi D_i + \Sigma v_i)$$

$$u_{ijt} = x_{jt}\beta - \alpha p_{jt} + \xi_{jt} + \left[p_{jt}, x_{jt} \right]' (\Pi D_i + \Sigma v_i) + \varepsilon_{ijt}$$

The mean utility, δ_{jt}, measures utility enjoyed by all consumers of product j in market t. Where μ_{ijt} adds utility specific to the ith consumer of product j in market t. As before, ε_{ijt} is the logistic error specific to the ith consumer of product j in market t. Assuming independence of consumer preference, δ_{jt}, for a given set of product characteristics, per Berry (1994) and Nevo (2000), market share of product j is

$$\begin{aligned} s_{jt}(x, p_{.t}, \delta_{.t}; \theta_2) &= \int_{A_{jt}} dP(D, v, \varepsilon) \\ &= \int_{A_{jt}} dP_\varepsilon(\varepsilon)\, dP_v(v) dP_D(D) \end{aligned} \tag{5.4}$$

$$A_{jt}(x, p_{.t}, \delta_{.t}; \theta_2) = \left\{ (D_i v_i \varepsilon_{it}) \middle| \mu_{ijt} \geq \mu_{ilt} \right\}, \forall l = 1, \ldots J$$

With distribution assumptions for the unobserved individual attributes, v and D, market shares are then derived from integrating ε out of equation 5.4 leaving the logit probabilities as a function of product features, price, mean utility and θ_2.

$$s_{jt}\left(x_{jt}, \delta_{jt}, \theta_2\right) = \frac{1}{ns} \sum_{i=1}^{ns} \frac{exp\left(\delta_{jt} + u_{ijt}\right)}{\sum_{j=1}^{J} \exp\left(\delta_{jt} + u_{ijt}\right)} \tag{5.5}$$

As noted in Berry (1994) the presence of ξ_{jt} in δ_{jt} implies endogeneity of prices given consumers observe those characteristics. Many works add endogeneity by including outside instruments z_{jt} assuming:

$$E\left[\xi_{jt} | x_{jt}, z_{jt}\right] = 0 \tag{5.6}$$

Mean utility, δ, can be constructed by minimizing the difference in observed market shares S_t from predicted market shares for a give set of θ_2 parameters. (Nevo 2000), (Chidmi, Lopez and Cotterill 2005):

$$Min\|s_t(x, p_t, \delta_t; \theta_2) - S_t\| \tag{5.7}$$

Then, using Berry (1995) δ is calculated using:

$$\delta_{jt} = \ln S_{jt} - \ln s_{0t}\,(x, p_t, \delta_t; \theta_2) \tag{5.8}$$

where s_{0t} is the share of the outside good for a given value of vector θ_2. Once δ is derived, ξ can be calculated using:

$$\xi_{jt} = \delta_{jt} - x_{jt}\beta - \alpha p_{jt} \tag{5.9}$$

α and β are estimated using linear instrumental variables. The ξ_{jt} solution used parameters, data and demographic draws (Hollo 2010). The model can now be estimated using Generalized Method of Moments (GMM) assuming equation 5.6 holds.

The final $\hat{\beta}$ matrix used for interpretation is calculated under the assumption $E[\varepsilon|X] = 0$,

$$\hat{\beta} = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}\hat{d}, \qquad \hat{\xi} = \hat{y} - X\hat{B} \tag{5.10}$$

where X is a set of smartphone attributes that do not vary across quarter or metropolitian area, $\hat{d}$ is a vector of estimated coefficients for brand dummies ξ represents unobserved smartphone features, and Ω is the variance-covariance matrix of the estimates (Nevo 2000).

Using specifics from Nevo (2000), elasticities are derived by simulation using equation 2.11. The elasticity specification is independent of any specific functional

$$E_{\text{jkt}} = \frac{\partial s_{\text{jt}} p_{kt}}{\partial p_{kt} s_{jt}} = \begin{cases} -\dfrac{p_{jt}}{s_{jt}} \displaystyle\int \alpha_i s_{ijt}\left(1 - s_{ijt}\right) dP_D(D) dP_v(v) & \text{if } j = k \\ \dfrac{p_{kt}}{s_{jt}} \displaystyle\int \alpha_i s_{ijt} s_{ikt}\, dP_D(D) dP_v(v) & otherwise \end{cases} \tag{5.11}$$

form. E_{jkt} also has the property of separating customer specific own-price calculations from share size.

5.3 BLP Smartphone Data

5.3.1 BLP Data Aggregation

Observations for BLP estimation were calculated by aggregating smartphone data across the 30 metropolitan areas selected for this study, across six quarters. The demographic draws used for BLP estimation were randomly selected from the respondent level self-reported income and presence of children in the household questions asked in the Nielsen Mobility Insights survey. These demographic questions and response specifics are found in Figure 3.1. Using the smartphone definition noted previously with Nielsen respondents age 18 and over, within the selected 30 metros, the sample equals 63,883 observations facing 1,291,189 choice alternatives for the consumer specific estimation. Aggregating the data by metropolitan area, quarter and smartphone model potentially yields 4,500 observations ($t = metro \cdot quarter = 30 \cdot 6$ multiplied by $j = 25$ phones for BLP estimation).

Market shares are calculated by summing the Nielsen Mobility Insight survey responses by smartphone, then dividing by the total number of smartphone respondents within a given metropolitan area and quarter combination. The outside good was calculated by subtracting smartphone shares from one. Table 5.1 illustrates the variation in smartphone market share across selected metros.

Table 5.1 Select Market Shares, 2013

Device	New York	Dallas	Miami	Seattle	Los Angeles	Chicago
iPhone 4S	19.10%	14.90%	16.50%	15.40%	17.30%	13.60%
iPhone 4	15.80%	15.70%	12.70%	13.00%	15.30%	13.90%
iPhone 5	12.20%	11.00%	13.40%	7.70%	11.70%	10.30%
Galaxy S III	9.20%	10.00%	9.50%	8.10%	8.10%	10.40%
Gaxaly S II	2.60%	4.10%	3.40%	3.80%	2.70%	3.60%
Galaxy S4	1.70%	2.00%	1.70%	1.60%	1.40%	2.10%
HTC Evo 4G	1.20%	1.80%	1.80%	1.20%	1.40%	1.70%
Galaxy Note II	2.30%	1.70%	1.80%	1.30%	1.80%	2.40%
Droid RAZR	1.40%	0.60%	0.30%	1.20%	1.20%	1.20%
Droid RAZR M	0.70%	0.30%	0.10%	0.80%	0.70%	0.60%
Droid RAZR X	0.50%	0.30%	0.30%	0.60%	1.10%	0.60%
Droid RAZR MAXX	0.90%	0.20%	0.60%	0.90%	1.00%	1.00%
Galaxy Nexus	0.90%	0.70%	0.80%	0.70%	1.00%	0.90%
HTC Inspire 4G	0.50%	1.20%	0.90%	0.50%	0.70%	1.50%

Source: Nielsen Mobility Insights Survey, 2013

During the study period, third quarter of 2012 to fourth quarter of 2013, iPhone and Samsung Galaxy models held the top six share places. All of these smartphone models demonstrate good share variation across metropolitan areas, but generally keep the same ranking.

5.3.2 Instrumental Variables

Conducting a Hausman test reveals that smartphone prices are endogenous within this BLP model specification (J. A. Hausman 1978) as the ρ in equation 5.12 is found to be statistically significant at $\alpha = 0.05$. z_{jt} denotes the instrumental variables discussed later in this section.

$$\boldsymbol{s_{jt} = \alpha + \beta_0 p_{jt} + \sum \beta_k x_{jt} + \rho\left(p_{jt} - \sum b_k z_{jt}\right) + u_{jt}} \tag{5.12}$$

Smartphone price endogeneity requires implementation of instrumental variables on smartphone price during the estimation procedure. Finding a quality instrumental variable for smartphone price that does not violate equation 5.6 or $E\left[\xi_{jt} | x_{jt}, z_{jt}\right] = 0$ proved difficult (Nevo 2000; Hahn and Hausman 2003). There are three standard conventions to find quality instrumental variables. One proposed by Berry, Levinsohn, and Pakes (1995) uses the premise that prices for specific smartphone models are correlated with features and prices of competing smartphones in the marketplace. (J. A. Hausman 2004) and (Nevo 2001) proposed using prices from other markets that do not share demand events with markets used for analysis. Unfortunately, the smartphone market rarely has market specific demand events, and certainly the industry does not have enough market level demand events to create a valuable instrumental variable for smartphone price. Nevo (2000) recommends finding cost variables that may put non-demand related pricing pressure on firms. Given the competitive nature of firms operating in this differentiated oligopoly market, finding smartphone cost variables that change by model, or even firm, was virtually impossible. Most instrumental variables

used for estimation vary across metropolitan area and time but not by smartphone brand or model.

Instrumental variables for smartphone price in the BLP estimation included key industry cost metrics such as production cost, marketing cost, and relevant producer price indices crossed with brand dummies to create cost variation across quarters and metro for each of the smartphone model. The manufacturing cost of most phones was calculated using a one-time teardown cost assessment from Techinsights. Techinsights had phone specific manufacturing cost estimates for eleven of the twenty five smartphones. Cost information for each of the other fourteen smartphones used manufacturing costs of like phones, Samsung Galaxy SII and Samsung Galaxy S III, along with other public intelligence (the Samsung Galaxy S III cost 15% more to manufacture) to derive cost estimates. Advertising GRP Gross Rating Points (GRP) from Media Edge Company (MEC) was used as a proxy for brand specific marketing cost. Television advertising within the cellular phone industry is summarized in Table 5.2. Note that advertising data are in aggregate and isn't specific to the smartphone model but to brand only. The base advertising metric is Gross Rating Points (GRP) for viewers 18 to 49 years old.

Table 5.2 Broadcast Advertising by Brand and Quarter, 2013 GRP

	Y13Q1	Y13Q2	Y13Q3	Y13Q4
AT&T	230,436	215,056	190,079	246,058
Verizon	114,515	125,485	127,646	235,831
T-Mobile	70,427	100,297	100,909	152,303
Sprint	73,751	67,111	62,190	142,259
Apple	83,732	42,423	48,144	163,307
Samsung	57,539	32,753	43,477	112,342
Motorola	555	0	21,678	107,776
HTC	34	60,251	19,900	3,150
LG	2,217	90	9,826	95,991
Blackberry	10,584	15,099	22,135	0
Nokia	771	35,622	59,289	63,108

Source: Nationalized TV Activity, Nielsen Media Research and MEC

Contract length, wireless network service provider price and smartphone age are meaningful variables pulled from the Nielsen Mobility Insight survey results which should have an impact on phone price. To account for other costs in business the Bureau of Labor Statistics producer price indices for transportation, retail trade services, and the unemployment rate were added as instrumental variables by crossing each with brand dummies. In all, 84 instrumental variables were used for estimation.

5.4 Smartphone BLP Results

Several data issues resulted in the actual aggregated observations being less than 4,500. Sample for low market share phones in small metropolitan areas and the addition of new phones during the six quarter time horizon collectively reduced the sample to 3,365. These data issues also lead to unbalanced choice sets across both quarters and metropolitan areas. For example, the choice set in early quarters do not include phones introduced in later quarters. The unbalanced choice set required the creation of a

"tracking vector" within the estimation to signal different smartphone choice sets across metropolitan area-quarter combinations, a process not commonly used in BLP estimation.

While the smartphone data yielded BLP estimated beta and sigma coefficients for smartphone price and smartphone features noted in Table 5.3, these results are from a model that failed to converge. The coefficients illustrated in Table 5.3 are from a late iteration outcome.

Table 5.3 BLP Estimated Coefficients

Variables		Estimate	t-values
Price:	Mean Beta	-3.8746	28.8718
	Sigma	-3.0800	22.9508
Screen Size:	Mean Beta	-3.1957	0.7518
	Sigma	0.0012	0.0126
Talk Time:	Mean Beta	163.56	7.3102
	Sigma	1.8850	22.2427
Weight	Mean Beta	-3.0366	0.0107
	Sigma	-3.0439	24.8482

The mean beta associated with smartphone price is negative and both the mean price beta and sigma are statistically significant at $\alpha = 0.05$, suggesting that households have heterogeneous reactions to changes in smartphone price. Neither the mean beta or sigma for smartphone screen size pass a significance test at $\alpha = 0.05$. Smartphone weight also seems to be a factor when making a phone purchase. Within the twenty five smartphone choice sets used for analysis, smartphone weight only averaged approximately 138 grams with the heaviest being 180 grams**.** Smartphone talk time – a consumer observed proxy for overall battery life – mean beta and sigma estimates are statistically significant at $\alpha = 0.05$. This suggests household purchase reaction to smartphone battery life is different for each household. Households all have different needs, with some examples being: time period between charges, power intensive applications, need for regular Wi-Fi access, or Bluetooth device linking. Each of these can impact the need for battery life, and all are unobserved in the data.

The resulting estimated BLP coefficients are used to calculate corresponding own-price and cross-price elasticities of demand using calculates from equation 5.11.

Own-price elasticities of three smartphone models were calculated and illustrated in Table 5.4. The three smartphones used are those with the highest market share during the research time horizon, and considered close substitutes within the higher priced smartphone segment. The BLP own-price elasticities are much larger than elasticities calculated from the mixed logit estimation illustrated in Table 4.4 and the elasticities from the BLP model are more similar across each of the three smartphones. However, the rank order remains the same. The newest Samsung Galaxy S III has the highest overall elasticity among the three phones followed by the older Apple iPhone 4S, no longer the newest iPhone, given the introduction of the iPhone 5. Own-price elasticity of demand for the iPhone 4 is lower given its age behind two newer Apple iPhone and several new Samsung Galaxy models. This can partially be explained by Apple providing a large discount on the iPhone 4 once the iPhone 5 entered the market during the fourth quarter of 2012.

Table 5.4 BLP Own Price Elasticities

Phone Model	Elasticity
iPhone 4S	-0.6618
Samsung S III	-0.6836
iPhone 4	-0.4895

Cross-price elasticities for these three smartphone models are illustrated in Table 5.5. Again, the BLP estimates yield higher elasticities than were estimated via the mixed logit. Cross-price elasticities from both estimation methods show the iPhone 4S and iPhone 4 as closer substitutes compared to the Samsung S III. This suggests that both

estimation methods found consumers seem to generally stay within a specific smartphone brand portfolio.

Table 5.5 BLP Cross-price Elasticities

	iPhone 4S	Samsung S III
Samsung S III	0.1326	
iPhone 4	0.1290	0.0556

The BLP estimate results imply own-price and cross-price elasticities of demand are consistent with accepted demand theory with negative own-price and positive cross-price elasticities for substitutable products. Elasticities also suggest that demand for high end smartphones is highly cross-price inelastic as consumers seem generally unmotivated to switch once they select a smartphone brand family. Note the older Apple iPhone 4 is not at all a good substitute for the newer Samsung Galaxy S III with cross-price elasticity of only 0.0556.

CHAPTER VI

COMPLEMENT BLP

The BLP model in Chapter V estimated smartphone model shares using smartphone price and three consumer noticed features: weight, talk time – a proxy for battery duration experienced by consumers – and screen size. During the period of analysis, wireless network providers often linked the smartphone purchase to a wireless network commitment with the intent to reduce initial customer smartphone expense by amortizing some or all of the smartphone expense over the length of a service contract. This marketing tactic links wireless network monthly cost and smartphone cost in two critical aspects. First, to get the full benefit of the smartphone, consumers need access to a wireless network. Second, the contractual obligation some customers maintain in order to enjoy a lower smartphone cost at time of purchase (Cromar 2010) creates a utility and legal bond with a given wireless network service provider.

The near perfect complementary nature of smartphones and wireless networks isn't new to the BLP empirical modeling. The original BLP paper analyzing automobiles included the price of gas as an explanatory variable for choosing a given automobile model (Berry, Levinsohn and Pakes 1995)

Models estimated to explain choice of cereal brand included supermarket brand (Chidmi and Lopez 2007). The model proposed in this chapter varies from most other models by having a branded and priced complementary product. For example, the Berry, Levinsohn and Pakes (1995) paper includes gas as an explanatory variable but only as a market aggregate. The BLP model did not have Texaco, Shell or Chevron gas, nor

should it, as gas brand likely plays no role in automobile choice. As for breakfast cereal, supermarket brand should matter but rarely do consumers pay for access to a supermarket. While breakfast cereal has many complements (e.g. milk, juice, and fruit), generally most consumers will purchase breakfast cereal regardless of the brand of milk in the store. In the cellular phone market the great majority of smartphone consumers also chose a wireless network provider, often based on which brand maximizes the utilitarian nature of the smartphone or provides hedonic features in consumption. A utilitarian example could simply be perceived network coverage in a specific area.

Section 6.1 provides a historical review of the theory and empirical modeling completed to understand consumer behavior when faced with branded complement choice. Section 6.2 introduces the methodology specific to the smartphone and wireless network service industry. Section 6.3 describes combining smartphone models and wireless network brands to create a share specific to a given smartphone and wireless network combination, and how this could improve model specification. The new model "complement BLP" now includes smartphone price, carrier price, and smartphone features as explanatory variables in a BLP estimation. Section 6.4 summarizes the estimation results for both the original smartphone-only BLP model and the complement BLP model. Reviewing own-price and cross-price demand elasticity differences should provide insight about the complementary nature of the smartphone models used with specific wireless network service provider brands.

6.1 Branded Complement Consumer Demand Historical Review

6.1.1 Branded Complement Literature

Historically, many companies have sold products that require a perfect or near perfect complement. Examples include automobiles and gasoline, cameras and film and currently smartphones and a wireless network (Hirschey 2009). Often, these complements each have consumer recognizable independent brands. Some examples are a Pontiac Tempest automobile and Texaco gasoline or the smartphone iPhone 4S and wireless network services provider Verizon. Most empirical work uses consumer level data to estimate the degree to which branded products are complementary (Berry, Khwaja, et al. 2014). A widely cited 1991 study by Walters collected grocery store scanner data as several stores varied price under experimental design within a controlled trial. Results show a price reduction via promotion increased sales of a given cake mix brand at the expense of other brands in the category. The study also revealed that increased brand sales from a promotion may also increase sales in a complementary branded category like cake frosting (Walters 1991). Results of the study also indicate that complementary effects can be asymmetric. For example, the complementary effect of a price change for a specific cake mix on cake frosting sales may be different than the complementary effect of a specific cake frosting brand price change on the sales of a brand of cake mix. The complementary effects are even stronger for cross category, same brand products.

Manchanda, Ansari, and Gupta (1999) greatly extended earlier work by developing a choice model that included key elements in a branded complementary

product purchase environment. The work considered issues of "Co-incidence" or reasons why a person may or may not purchase different category items during a shopping trip (e.g. issues such as transportation cost or a time constraint for a given trip to the market, or a crowded store). The work also considered how consumer differences or heterogeneity of the household impacts the own effect and cross effects of a branded purchase. Data were collected from a syndicated source over 120 weeks of shopping trips and estimated with probit using a general consumer utilities theory framework. The Manchanda, Ansari, and Gupta (1999) results are consistent with earlier work. Own-price effects were larger than cross-price effects, and cross-price effects were asymmetric. For example, price changes for detergent impact fabric softener sales more than fabric softener prices impact detergent sales.

Lee, Kim and Allenby (2013) continued to investigate asymmetric complements by investigating products hypothesized to be asymmetric, like milk and cereal. The study found consumer react to sales stimuli in different ways and consumers rationally inventory less milk and more cereal.

The relationship between smartphone models and wireless network service providers could potentially be asymmetric, especially across brands. A consumer using an Apple iPhone 4 has some options to switch between wireless network service providers while keeping the iPhone 4. Manchanda, Ansari, and Gupta (1999) also found that household heterogeneity does play a role in price sensitively for different product categories. Co-incidence of purchase for a given shopping trip is in some part dependent of the product categories. Cake mix and cake frosting are quite often purchased on the

same trip while detergent and fabric softener are more independent. The study analyzed a key issue – household heterogeneity – in the context of branded complements, and found household demographics likely impact the purchase of many branded products. It is likely, then, that household difference also impacts the joint smartphone / wireless network service provider decision as well.

6.1.2 Branded Product Topical Literature

Cellular phone manufacturers and wireless network providers employ standard network effect tactics to improve sales and reduce consumer choice (Shy 2011). Manufactures add physical features and wireless network features that only communicate with like branded phones. Wireless network service providers employee joint usage pricing structures. Both include cloud services which may have network effect elements.

Branded products and services from national companies often require advertising to inform and remind consumers about availability. Many studies have attempted to link advertising exposure to product choice using standard utility models (D. A. Ackerberg 2003) (Anand and Shachar 2011). Some literature hypothesizes that prolonged exposure to high cost advertising signals quality to consumers (Nelson 1974) (Milgrom and Roberts 1986). Each industry participant has regular product or service upgrades. Such information must be disseminated into the market quickly for best sales results. Cellular phone manufactures often have important product updates on less than an annual cycle, while wireless network providers run discretionary promotions and change service features regularly, which requires regular advertising. Most cellular phone manufacturers

and wireless network service providers also maintain a consistent brand presence using national advertising to remain in a consumer choice set when the selection process begins.

In the early days, wireless network pricing was largely usage based. Most consumers paid a monthly network access fee plus a usage based conversation minutes fee. As the cellular industry grew, new services were added, with texting and internet access being the two most popular additions in the last decade. As competition for subscribers grew, wireless network providers began to offer new price options. By the analysis period for this study, many wireless network providers were offering a wide range of options: a flat price for a fixed block of usage, packaged offers such as free texting with a fixed minutes of use purchase, as well as a number of other options. The new offers have created, for some consumers, an indivisibility problem (Lee and Allenby 2014) (Allenby, et al. 2004). Some consumers may like and want to purchase a phone / wireless network combination, but the fixed set of current offers are not appealing enough for purchase. Lee and Allenby (2014) show models designed to predict choice should consider adding indivisible usage and corresponding pricing structures into the specification. This could be a flaw in our specification as the data do not separate consumer choice conditions into the specific indivisible services they purchased or could have purchased.

There is a large thread of marketing literature supporting the original McFadden work of using product features as independent variables to avoid the dimensionality problem when estimating a consumer choice demand model. Notable works consider a

product as the collection of features or attributes which are the ultimate conduit to consumption utility (Aaker 1996) (K. L. Keller 1998).

6.1.3 Branded Complement Literature Discussion

The great bulk of existing literature focusing on consumer choice of branded product and services focus on the emotional elements, and are most often published in marketing or advertising journals. While most marketing research uses economic utility theory as a foundation, few extend to elasticity calculations, analysis and discussion. The model outlined in this chapter will continue with the notion of choice as a function of price, a set of important consumer noticed features and basic demographics.

Most all empirical branded complement work was completed using a task specific experimentally designed sample, collected via consumer survey, a product trial, or a combination of the two. Few studies have used aggregate data to examine the own and cross price effects of branded complements. This chapter outlines the methodology and aggregated data used to estimate a BLP model with sets of branded complements, then examines the market share impact price changes may have on not only the product category, smartphones and wireless networks, but also specific smartphone models and branded wireless networks; an Apple iPhone 4S on the Verizon wireless network.

6.2 Methodology Introduction

The first BLP model of the smartphone industry in chapter V was estimated using twenty-five smartphone shares calculated over six quarters and thirty metropolitan areas. Along with smartphone shares, smartphone average price, basic smartphone features and random draws of widely accepted demographic variables are used to create data for estimation. The "smartphone only BLP" specification fails to include a large portion of the smartphone market. During the analysis period, third quarter 2012 to fourth quarter 2013, most plans subsidized much of the smartphone cost into the network provider monthly recurring charge. Most often consumers choosing to purchase a smartphone at full cost did not even get monthly recurring charge relief. This pricing protocol contractually linked already near perfect substitutes by partnering to pay for the smartphone. A typical arrangement may require the consumer to pay a share of the smartphone cost, possibly 1/3, while the wireless network provider covered the remaining 2/3 cost by loading the cost into the monthly recurring charge. This initial purchase point smartphone price reduction then requires an agreement between the consumer and wireless network service provider sufficiently long enough to recover the remaining smartphone cost.

The new model or "complement BLP," using both the smartphone price and network service provider price, was estimated using shares calculated from the joint smartphone and wireless network service provider construct. The model treats a phone and wireless network provider combination as one product when calculating market shares. For example, the iPhone 4 / Verizon combination will be considered one product

share across each quarter and metropolitan area. The new "complement BLP" model is summarized and compared with the chapter V "smartphone only BLP" model estimated with only smartphone model shares. This new data construct should allow the BLP model to more appropriately associate smartphone initial consumer cost to choice. Any meaningful difference should show up as deviations from the "smartphone only BLP" and this "complementary BLP" model.

6.3 Branded Complement BLP Model

The smartphone industry allows for the introduction of strongly related brand differentiated complementary products. Adding a complement price, even a perfect complement, isn't new to BLP. Berry's original paper included gas price as a generic perfect complementary commodity to automobiles. In this section the complement product has a price with brand identity relevant to consumers. Starting from the original 6.1 equation:

$$u_{ijt} = x_{jt}\beta_i - \alpha_i p_{jt} + \xi_{jt} + \varepsilon_{ijt} \tag{6.1}$$

where i is a specific consumer, $j = j_h \cdot j_c$ now represents a smartphone-carrier set (iPhone 4S paired with AT&T or Samsung Galaxy S3 paired with Verizon) where t is the market identifier. x_{jt} are a set smartphone features observed by the analyst, p_{jt} is a new set prices for both smartphone hardware $p_{j_h t}$ and carriers $p_{j_c t}$ in market t, ξ_{jt} represents the unobserved to the analyst product and carrier characteristics in market t. Moving through the BLP framework leads to a revised equation 6.2. The carrier price, $p_{j_c t}$, is not treated with IV, while smartphone price, $p_{j_h t}$, is treated as documented in section V.

$$u_{ijt} = \delta_{jt}\left(x_{jt}, p_{j_h t}, p_{j_c t}\, \xi_{jt}; \theta_1\right) + \mu_{ijt}\left(x_{jt}, p_{j_h t}, p_{j_c t}, D_i, v_i; \theta_2\right) + \varepsilon_{ijt} \tag{6.2}$$

The wireless network service provider price was calculated from the Nielsen Mobility Insights survey by finding the average carrier price of service for each smartphone across quarter and metropolitan area. The specific survey questions are "Who is your current primary cell phone service provider?" and "On average, what is the total amount you actually spend on your cell phone service (including roaming, long distance and all other additional charges) per month? If you have a family plan please include the amount spent on all lines."

The choice set within each quarter / area combination increased to 100 $j = j_h \cdot j_c$, or twenty five smartphones potentially sold across four national wireless carriers. While the Nielsen Mobility Insights survey collects approximately 90,000 completed interviews per quarter, defining shares, smartphone price and carrier price to a potential 100 combinations per metropolitan area proved impossible. To resolve this issue the original 30 metropolitan areas were combined into five broader regions noted in Table 6.1.

Table 6.1 Regional Aggregation

NE	SE	MW	SW	W
Boston	Atlanta	Chicago	Dallas	Los Angeles
New York	Miami	Detroit	Houston	San Francisco
Philadelphia	Charlotte	Indianapolis	Denver	Las Vegas
Washington	Orlando	Minneapolis	Kansas City	Portland
Baltimore	Tampa	Cincinnati	Phoenix	San Diego
		Columbus	St. Louis	Seattle
			San Antonio	Sacramento

Recall the earlier BLP model used smartphone share data from the Nielsen Mobility Insights survey from a 30 metropolitan areas sample totaling 63,883 observations. Aggregating the data by metro, quarter and smartphones yielded 4,500 observations $t = metro \cdot quarter = 30 \cdot 6$ multiplied by $j = 25$ phones for BLP estimation. Market shares were calculated by summing the Nielsen responses by smartphone then dividing by total number of smartphone respondents within a given metro and quarter combination. The outside good was calculated by subtracting smartphone shares from one. Table 5.1 illustrates variation in smartphone market share across selected metros.

The Nielsen data was aggregated by quarter, region, and smartphone / carrier combination yielding 3,000 observations $t = region \cdot quarter = 5 \cdot 6 = 30$ multiplied by $j = j_h \cdot j_c = 4 \cdot 25 = 100$ per region / quarter.

A partial data for the West Region, fourth quarter of 2013 for smartphones (iPhone 4S, iPhone 4, and Samsung S III) paired with two carriers (AT&T and Verizon) are illustrated in Table 6.2.

Table 6.2 Smartphone Carrier Combinations Summary

West Region, Fourth Quarter 2013			
Smartphone / Carrier	Share	Smartphone Price	Network Price
iPhone 4S / AT&T	5.3%	$158.80	$144.93
iPhone 4S / Verizon	3.8%	$190.17	$149.93
iPhone 4 / AT&T	3.8%	$144.91	$134.72
iPhone 4 / Verizon	3.4%	$104.04	$150.14
Samsung S III / AT&T	1.1%	$137.44	$140.22
Samsung S III / Verizon	2.7%	$125.98	$141.58

Source: Nielsen Mobility Insight Survey, 2013

The first row in table 6.2 reads as: the Apple iPhone 4S on the AT&T wireless network in the fourth quarter of 2013 had 5.3% market share with the iPhone 4S. The average price was $158.80 when on the AT&T network and the cost of access to the AT&T wireless network for consumers using an iPhone 4S was $144.93 during the fourth quarter of 2013 in the west region.

Instrumental variables for price are as before, using industry cost metrics such as production cost, marketing proxy cost, and relevant producer price indices crossed with brand dummies to create cost variation across quarters and region for each smartphone model / wireless network provider combination. The manufacturing cost of most phones was calculated using a one-time teardown cost assessment from Techinsights as detailed in chapter V, section 5.3. Advertising Gross Rating Points (GRP) from Media Edge Company (MEC) was used as a proxy for brand specific marketing cost, now includes both companies that produce smartphones and GRP data for wireless network service providers as detailed in chapter V, section 5.3, Table 5.2. Contract length and phone age are meaningful variables pulled from the Nielsen Mobility Insight survey results which should have an impact on the smartphone model price. And as before, data from the Bureau of Labor Statistics – producer price indices for transportation, retail trade services and the unemployment rate – were added as instrumental variables by crossing each with brand dummies as a proxy for cost. The wireless network price is no longer an instrumental variable as it now enters the primary demand equation. Brand dummies are now smartphone / wireless network provider specific dummies.

Several data issues lead to the actual aggregated observations being less than 3,000. Sample for low market share smartphone/carrier combinations and the addition of new smartphones during the six quarter time horizon collectively reduced the sample to 1,206. The data again has unbalanced choice sets across the markets.

6.4 Branded Complement BLP Results

Results from the branded complement BLP model which includes branded complement network provider prices are illustrated and discussed in this section. As with the "smartphone only BLP" the model did not converge and estimates are from a specific late iteration**.** The smartphone price, wireless network carrier price and feature specific estimated coefficients are illustrated in Table 6.3.

Table 6.3 Complement BLP Coefficients

Variables		estimate	t-values
Phone Price	Mean Beta	-2.5672	30.6714
	Sigma	0.0054	0.0382
Carrier Price	Mean Beta	5.9283	undefined
	Sigma	0.0034	undefined
Screen Size	Mean Beta	3.1012	4.2959
	Sigma	0.0039	0.0299
Talk Time	Mean Beta	-1.4551	0.0061
	Sigma	-0.0099	0.0759
Weight	Mean Beta	-1.5543	0.1864
	Sigma	-0.0000	undefined

The signs on the parameter estimates for both screen size and talk time are different from the "smartphone only BLP in chapter V. The smartphone price coefficient drops in absolute value from -3.8746 in the smartphone only model to -2.5672 in the complement model noted above. Smartphone sigma is not statistically significant indicating on

average most households react in approximately the same level as smartphone price changes.

By using the elasticity equation, 5.11, own-price and cross-price elasticities of only three smartphones were calculated to abbreviate the illustration. Only the iPhone 4S, the iPhone 4 and the Samsung S III are illustrated in Table 6.4.

Table 6.4 Smartphone Price Elasticity Comparison

	Smartphone BLP	Complement BLP	
	Smartphone Price	Smartphone Price	Wireless Carrier Price
iPhone 4S	-0.6618	-0.5028	-0.3202
Samsung S III	-0.6836	-0.4364	-0.3513
iPhone 4	-0.4895	-0.3642	-0.3214

The complement BLP model has lower overall own-price elasticities compared with the smartphone only BLP model without wireless network provider specifics. The complement model now has the added wireless network provider pricing impact on smartphone share. Smartphone shares for the Apple iPhone 4S are determined by smartphone price elasticity and wireless network provider price elasticity, -0.5028 and -0.3202 respectively. Differences in data aggregation used to estimate each model, specifically aggregating metropolitan areas into regions, reduced the price variation for any given smartphone. This could be the result of larger sample within a given region, but it could be market related, as smartphone prices within any given wireless network provider brand has less variance because the smartphone model price is averaged across all brands, meaning no wireless network provider specific data. This suggests that carriers each practice stable pricing policies for a given smartphone sold in combination with

their wireless network brand. The iPhone 4S price and share variance for the smartphone only model in the fourth quarter of 2013 was $373.49 and 0.0003 respectively. The comparable iPhone 4S in the same quarter connected to the AT&T network was $56.12 and virtually zero respectively. Elasticities are much higher for the iPhone 4S relative to the iPhone 4 in both models. Again the iPhone 4S being the newer, higher priced smartphone in the market compared to the iPhone 4 likely caused consumers to be more price sensitive to the iPhone 4S. The iPhone 4S in the third quarter of 2012 had an average price of $225.87, and by the fourth quarter of 2013 the average price had dropped to $164.47. The Samsung S III has a lower own-price elasticity compared with the iPhone 4S in the complement BLP, but has the highest wireless provider price elasticity in the complementary model.

Own-price smartphone elasticities from the complement BLP across the all four wireless network providers are calculated and illustrated in Table 6.5.

Table 6.5 Smartphone Own Price Elasticity from the Complement BLP

	iPhone 4S	Samsung S III	iPhone 4
Market	-0.5028	-0.4364	-0.3642
AT&T	-0.4258	-0.3826	-0.3411
Verizon	-0.4280	-0.3999	-0.2938
T-Mobile	-0.7334	-0.6200	-0.5815
Sprint	-0.4331	-0.3411	-0.2403

The iPhone 4S generally has a higher price and a higher own-price elasticity relative to the close substitutes (Samsung S III and iPhone 4). A review of carrier differences shows T-Mobile with much higher own-price elasticities across each smartphone as compared with AT&T, Verizon, or Sprint. The older smartphone and lower priced, iPhone 4, has

lower elasticities across all four carrier brands. The market smartphone own-price elasticities calculated from the complement BLP are noticeability lower relative to the earlier smartphone only BLP smartphone own-price elasticities illustrated in Table 5.4.

The carrier price impact on smartphone share can also be reported at the brand level. Table 6.6 illustrates these carrier brand elasticity results. While the Apple iPhone 4S smartphone own price elasticity is highest on the T-Mobile network, the carrier price elasticity is lowest for T-Mobile.

Table 6.6 Smartphone, Network Carrier Price Elasticity from the Complement BLP

	iPhone 4S	Samsung S III	iPhone 4
Market	-0.3202	-0.3513	-0.3214
AT&T	-0.3312	-0.3603	-0.3182
Verizon	-0.3545	-0.3666	-0.3459
T-Mobile	-0.2589	-0.3185	-0.2735
Sprint	-0.3342	-0.3597	-0.3481

The smartphone and network provider price elasticity dispersion about the mean elasticities, Table 6.7, show smartphone own-price elasticities have more movement from household to household than does the wireless network provider cross price elasticity. Generally, smartphone prices change as the result of new phone introduction promotion periods, older model discounting, quantity discounting, and many other promotion techniques. While wireless carrier promotions often are not pricing based:

Table 6.7 Smartphone and Carrier Price Elasticity Standard Deviations

	Smartphone Mean Elasticity	Smartphone Std. Dev. Elasticity	Carrier Mean Elasticity	Carrier Std. Dev. Elasticity
iPhone 4S	-0.5027	0.1949	-0.3202	0.0652
iPhone 4	-0.3642	0.1623	-0.3214	0.0612
Galaxy S III	-0.4364	0.1410	-0.3513	0.0485

extra data or unlimited talk time minutes are two population promotions which provider added value to the consumer within price discounting.

Cross-price elasticities for each smartphone model (iPhone 4S, iPhone 4, and Samsung SIII) are calculated and illustrated in Table 6.8. The "smartphone only BLP" without carrier specifics show that phone models are generally cross-price inelastic but suggests the iPhone 4S is more cross-price sensitive than both the Samsung S III or the iPhone 4. Smartphone cross-price elasticities of demand calculated from the "complement BLP" are noticeably smaller than from the "smartphone only BLP".

Table 6.8 Cross-price Elasticity Complement BLP

	iPhone 4S	Samsung S III	iPhone 4
iPhone 4S		0.0210	0.0075
Samsung S III	0.0846		0.0732
iPhone 4	0.0297	0.0253	

The smaller cross-price elasticities between the Samsung Galaxy S III and both Apple iPhone could be, in part, the result of operating system switching costs (Colgate, et al. 2007) (Peng and Wang 2006) or networking tactics such as loss of brand related services (Shy 2011). Results in table 6.8 show asymmetric substitution as the older Apple iPhone

4 is a poor substitute for the newer smartphone models (Manchanda, Ansari and Gupta 1999).

Having a complement service to the smartphone, wireless network access, which has a separate price, allows a more complicated cross-price analysis. For example, we consider how substitutable an iPhone 4S on the AT&T network is to an iPhone 4S on the Verizon network, or how substitutable an iPhone 4S is with the Galaxy S III both on a Verizon network. This results are illustrated in Table 6.9 below.

Table 6.9 Own and Cross-price Elasticity Comparison for Complement BLP

	iPhone 4S / AT&T	iPhone 4S / Verizon	iPhone 4 / AT&T	iPhone 4 / Verizon	Samsung S III / AT&T	Samsung S III / Verizon
iPhone 4S / AT&T	-0.4258	0.0224	0.0257	0.0182	0.0041	0.0067
iPhone 4S / Verizon	0.0311	-0.4280	0.0258	0.0183	0.0041	0.0068
iPhone 4 / AT&T	0.0307	0.0223	-0.3411	0.0183	0.0038	0.0062
iPhone 4 / Verizon	0.0301	0.0225	0.0260	-0.2938	0.0039	0.0063
Samsung S III / AT&T	0.0313	0.0223	0.0247	0.0171	-0.3826	0.0186
Samsung S III / Verizon	0.0317	0.0225	0.0249	0.0173	0.0099	-0.3999

Interestingly a smartphone-carrier combination has lower elasticities across all three smartphones relative to the smartphone only BLP model elasticities. This result suggest carrier brand efforts result in lower smartphone specific own-price and cross-price elasticities.

CHAPTER VII

SUMMARY AND RECOMMENDATIONS

7.1 Final Comments

Chapter V investigated output from a BLP, aggregated data model, relative to a logit model estimated with respondent specific choice data. Using a large sample, continuous tracking survey, across six quarters and thirty metropolitan areas provided the platform to estimate both models with reasonably consistent data. The coefficient signs for price and each product feature remained consistent for both estimation methodologies. The BLP model generally had higher own-price and cross-price elasticities compared to elasticities derived from a consumer specific mixed logit.

Chapter VI attempted to extend the original smartphone only BLP model by adding the network connection perfect or near perfect complement and reducing data variation by aggregating the survey respondent level data to larger population areas. The network complement BLP model yielded noticeably different product feature coefficients compared with the original model. While smartphone price remained negative, the brand specific network complement price was estimated positive. The complement BLP yielded smaller overall smartphone price elasticities. Further, a given smartphone paired with a given network provider yielded even lower own-price elasticities, suggesting smartphone / carrier combinations are less price sensitive. During the time horizon of this analysis, carriers exercised some control over both carrier price and smartphone price via widely accepted contractual arrangements for the period. These contracts discounted

smartphones to carrier customers in return for extended commitments to remain with a given carrier.

In summary, using a BLP estimation method as an alternative when consumer level choice data does not exist, from an empirical level, seems perfectly valid. Both price and feature coefficient signs were consistent when using aggregates from consumer level data within the smartphone industry. Both BLP models estimated suffered from poor instrumental variables. It was difficult to find variables that varied across specific smartphones within given metropolitan area, quarter combinations.

7.2 Possible Extensions

7.2.1 Data Source

Chapter V compared BLP estimation to a consumer specific mixed logit by using a large sample tracking survey to generate aggregated data for BLP estimation while using the respondent level data to estimate the mixed logit. The tracking questionnaire did not include traditional choice based design which exposes each respondent to a set of smartphone price combinations. As such, the consumer level mixed logit did not have observed prices for each possible choice during a given quarter / area combination. In the future, hopefully, a researcher will be able to fund or find a large sample product tracker which has a product choice design within the questionnaire. This would improve the current paper in two ways. First, for each respondent, the researcher would benefit from having specific product, price combinations viewed, then acted on, by survey participants. Second the BLP can then be constructed with balanced choices across time

and space which would allow for a truer test between consumer level choice based models and BLP.

7.2.2 Instruments for Multiple Prices

Chapter VI added shares calculated across smartphone and carrier brand combinations. During estimation the theoretical endogeneity of smartphone price benefited for instrumental variables while the carrier price was added as a directly estimated random variable in the complement BLP. In the future estimating a model allowing both prices to benefit from instrumental variables should improve the theoretical validity for the complement BLP model.

7.2.3 Market Based Data

Another logical next step would be to integrate, where possible, market based data. For example both the smartphone and carrier price used for estimation in this work came from respondent self-reported prices from the Nielsen Mobility Insights survey. At the aggregate level it could be possible to find phone price and carrier price reports by a government agency, a third party organization, or by viewing product advertising. Estimating a new model using other market data sources could be enlightening.

For this work, to continue the theme of overall data consistency, demographic draws used for BLP estimation came from the Nielsen Mobility Insights survey. A new model estimating a BLP using government demographic data would allow another review

of BLP estimation relative to the mixed logit and the traditional, smartphone only, BLP discussed in both chapters V and VI.

Last smartphone market shares were also calculated using the Nielsen Mobility Insights survey, again to provide maximum data consistency when comparing BLP to the mixed logit. Estimating a BLP using publicity available industry shares could be interesting.

7.3 Industry Policy

While the data used for analysis in this work drew from a large sample survey which wasn't constructed to collect smartphone prices within an experimental design, using BLP allowed for product level estimation. Many other industries investigated using BLP allowed analysts the ability to understand basic industry dynamics including brand and product features observable to consumers (Samsung, LG, Apple, screen size, weight, talk time). BLP provides the ability to collect data for estimation using any potential data source in a highly cost effective and possibly time saving manner. Results from BLP can provide value to a firm within industry looking to understand current market positon or to a policy maker reviewing product or firm position within the overall market. BLP likely cannot explain the impact of a product concept yet introduced to market, but BLP may possibly provide limited insight to the loss of a product or firm in the current market environment. For the smartphone market, BLP found that a branded sales channel can impact the price sensitivity of a like product, in this case, a given smartphone model.

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APPENDIX A

THETA COEFFICIENTS FOR TRADITIONAL OF SMARTPHONE ONLY BLP

THETA ONES

	COEFFICIENT
Smartphone Price	-4.1834
Brand Dummies	
Apple iPhone 4S	-4.8007
Apple iPhone 4	-4.9761
Apple IPhone 5	-5.2089
Samsung Galaxy S III	-5.6472
Samsung Galaxy S II	-6.6712
Samsung Galaxy S4	-6.5718
Samsung Galaxy Note II	-7.0093
Apple iPhone 5S	-5.7843
Motorola Droid RAZR	-7.5906
HTC Evo 4G	-7.3600
Motorola Droid RAZR M	-8.1268
LG Motion 4G / Optimus Regard	-8.2723
Motorola Droid RAZR MAXX	-7.8658
Samsung Galaxy Nexus	-8.0540
Samsung Galaxy S Blaze 4G	-7.9980
HTC Evo 4G LTE	-8.3028
HTC One	-7.8732
Samsung Galaxy S 4G	-7.8958
Samsung Exhibit II 4G / Galaxy Exhibit 4G	-7.9777
Samsung Stratosphere	-8.3492
HTC Inspire 4G	-8.2368
Samsung Admire / Vitality	-7.7883
Motorola Droid Bionic	-8.2642
LG Lucid / Optimus Exceed	-8.6164
Motorola Droid X	-8.0219

THETA TWOS

	v	Constant	Income	Income^2	Age	Kids
Constant	-0.5890	0.1913	-0.1370	-1.0176	10.2882	-0.5319
Phone Price	-4.1962	1.1528	-0.7403	-2.604	3.6064	-1.1377
Screen Size	0.5997	0.2248	0.3649	-1.4753	0.2319	-0.5379
Weight	-1.3262	0.1911	-0.7889	-2.2327	0.2795	0.6113
Talk Time	1.7346	0.1911	0.2499	0.4126	0.4944	-1.8880

APPENDIX B

THETA COEFFICIENTS FOR COMPLEMENT BLP

THETA ONES

	COEFFICIENT
Smartphone Price	-2.5672
Carrier Price	37.0362
Smartphone / Carrier Dummies	
Apple iPhone 4S / AT&T	-9.3882
Apple iPhone 4S / Verizon	12.4953
Apple iPhone 4S / T-Mobile	0.1065
Apple iPhone 4S / Sprint	1.2895
Apple iPhone 4 / AT&T	-146.1532
Apple iPhone 4 / Verizon	147.5343
Apple iPhone 4 / T-Mobile	-4.45229
Apple iPhone 4 / Sprint	-0.07510
Apple iPhone 5 / AT&T	216.9761
Apple iPhone 5 / Verizon	-212.2012
Apple iPhone 5 / T-Mobile	3.5065
Samsung Galaxy S III / AT&T	-107.9504
Samsung Galaxy S III / Verizon	-0.4204
Samsung Galaxy S III / T-Mobile	84.0329
Samsung Galaxy S III / Sprint	6.50285
Samsung Galaxy S II / AT&T	108.6681
Samsung Galaxy S II / T-Mobile	-76.8696
Samsung Galaxy S II / Sprint	-12.4381
Samsung Galaxy S4 / AT&T	0.81590
Samsung Galaxy S4 / Verizon	1.04182
Samsung Galaxy S4 / Sprint	20.7171
Samsung Galaxy Note II / AT&T	-1.4646
Samsung Galaxy Note II / Verizon	-0.9328
Samsung Galaxy Note II / T-Mobile	-3.5594
Samsung Galaxy Note II / Sprint	-13.4455
Apple iPhone 5S / AT&T	-126.3110
Apple iPhone 5S / Verizon	124.7824

THETA TWOS

	v	Constant	Income	Income^2	Age	Kids
Constant	0.7551	-4.54270	-21.2275	0.0	-4.4704	0.4264
Phone Price	0.0054	4.1654	-1.9519	9.3426	-3.2436	-2.9184
Carrier Price	2.9753	1.2064	-9.3235	-6.5833	-2.0582	-1.2390
Screen Size	39.4078	-0.8098	-1.7362	0.0	0.0954	-2.0015
Weight	-1.8159	-9.8612	-16.7333	0.0	-3.8494	-0.7552
Talk Time	-99.2925	-68.4636	-3.6554	0.0	-24.8331	0.0

APPENDIX C

SPSS CODE FOR MEDIA DATA READ AND AGGREGATE

```
GET DATA /TYPE=XLSX /FILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Mec\TvGrpMobile.xlsx'
/SHEET=name 'Data' /CELLRANGE=full /READNAMES=on
/ASSUMEDSTRWIDTH=32767.
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Mec\MecGrpMobile.sav' .

GET DATA /TYPE=XLSX/FILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Mec\TvGrpOther.xlsx'
 /SHEET=name 'Data' /CELLRANGE=full /READNAMES=on
/ASSUMEDSTRWIDTH=32767.
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Mec\MecGrpOther.sav' .

GET FILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Mec\MecGrpMobile.sav' .
ADD FILES /FILE=* /FILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Mec\MecGrpOther.sav' .
IF (Year=2012 and Qtr=3) QtrN=51 .
IF (Year=2012 and Qtr=4) QtrN=52 .
IF (Year=2013 and Qtr=1) QtrN=53 .
IF (Year=2013 and Qtr=2) QtrN=54 .
IF (Year=2013 and Qtr=3) QtrN=55 .
IF (Year=2013 and Qtr=4) QtrN=56 .
IF (Year=2014 and Qtr=1) QtrN=57 .
EXECUTE .

IF (Company="AT&T") CompanyN=1 .
IF (Company="Verizon") CompanyN=2 .
IF (Company="T-Mobile") CompanyN=3 .
IF (Company="Sprint/Nextel") CompanyN=4 .
IF (Company="Apple") CompanyN=5 .
IF (Company="Samsung") CompanyN=6 .
IF (Company="Motorola") CompanyN=7 .
IF (Company="HTC") CompanyN=8 .
IF (Company="LG") CompanyN=9 .
```

```
IF (Company="Blackberry") CompanyN=10 .
IF (Company="Nokia") CompanyN=11 .
IF (Company="Panasonic") CompanyN=12 .
IF (Company="Pantech") CompanyN=13 .
IF (Company="Sony") CompanyN=14 .
EXECUTE .
RECODE CompanyN (SYSMIS=0) (ELSE=COPY) .
RECODE Grp_18_49 (CONVERT) INTO Grp1849 .
RECODE Grp_25_54 (CONVERT) INTO Grp2554 .
EXECUTE .
VARIABLE LABELS CompanyN 'Company' .
VALUE LABELS CompanyN 0 'All Other' 1 'AT&T' 2 'Verizon' 3 'T-Mobile' 4 'Sprint' 5
'Apple' 6 'Samsung' 7 'Motorola' 8 'HTC' 9 'LG' 10 'Blackberry' 11 'Nokia' 12 'Panasonic'
13 'Pantech' 14 'Sony' .
VALUE LABELS DmaN 500 'Portland-Auburn'  501 'New York'  502 'Binghamton'  503
'Macon'  504 'Philadelphia'  505 'Detroit'  506 'Boston (Manchester)'  507 'Savannah'  508
'Pittsburgh'  509 'Ft. Wayne'  510 'Cleveland-Akron (Canton)' 511 'Washington, DC
(Hagrstwn)'  512 'Baltimore'  513 'Flint-Saginaw-Bay City'  514 'Buffalo'  515 'Cincinnati'
516 'Erie' 517 'Charlotte'  518 'Greensboro-H.Point-W.Salem'  519 'Charleston, SC'  520
'Augusta'  521 'Providence-New Bedford' 522 'Columbus, GA' 523 'Burlington-
Plattsburgh' 524 'Atlanta'  525 'Albany, GA'  526 'Utica'  527 'Indianapolis' 528 'Miami-
Ft. Lauderdale'  529 'Louisville'  530 'Tallahassee-Thomasville'  531 'Tri-Cities, TN-VA'
532 'Albany-Schenectady-Troy' 533 'Hartford & New Haven'  534 'Orlando-Daytona
Bch-Melbrn' 535 'Columbus, OH'  536 'Youngstown'  537 'Bangor' 538 'Rochester, NY'
539 'Tampa-St. Pete (Sarasota)'  540 'Traverse City-Cadillac'  541 'Lexington'  542
'Dayton' 543 'Springfield-Holyoke'  544 'Norfolk-Portsmth-Newpt Nws'  545 'Greenville-
N.Bern-Washngtn'  546 'Columbia, SC' 547 'Toledo'  548 'West Palm Beach-Ft. Pierce'
549 'Watertown'  550 'Wilmington'  551 'Lansing'  552 'Presque Isle' 553 'Marquette ' 554
‘Wheeling-Steubenville'  555 'Syracuse'  556 'Richmond-Petersburg'  557 'Knoxville'  558
'Lima' 559 'Bluefield-Beckley-Oak Hill' 560 'Raleigh-Durham (Fayetvlle)'  561
'Jacksonville'  563 'Grand Rapids-Kalmzoo-B.Crk'  564 'Charleston-Huntington'  565 '
Elmira (Corning)'  566 ' Harrisburg-Lncstr-Leb-York'  567 ' Greenvll-Spart-Ashevll-And'
569 ' Harrisonburg'  570 'Myrtle Beach-Florence'  571 'Ft. Myers-Naples'  573 'Roanoke-
Lynchburg'  574 'Johnstown-Altoona' 575 'Chattanooga'  576 'Salisbury'  577 'Wilkes
Barre-Scranton'  581 'Terre Haute'  582 'Lafayette, IN'  583 'Alpena' 584 'Charlottesville'
588 'South Bend-Elkhart'  592 'Gainesville'  596 'Zanesville'  597 'Parkersburg'  598
'Clarksburg-Weston' 600 'Corpus Christi'  602 'Chicago'  603 'Joplin-Pittsburg'  604
'Columbia-Jefferson City'  605 'Topeka'  606 'Dothan' 609 'St. Louis'  610 'Rockford'  611
'Rochestr-Mason City-Austin'  612 'Shreveport'  613 'Minneapolis-St. Paul'  616 'Kansas
```

City' 617 'Milwaukee' 618 'Houston' 619 'Springfield, MO' 622 'New Orleans' 623 'Dallas-Ft. Worth' 624 'Sioux City' 625 'Waco-Temple-Bryan' 626 'Victoria' 627 'Wichita Falls & Lawton' 628 'Monroe-El Dorado' 630 'Birmingham (Ann, Tusc)' 631 'Ottumwa-Kirksville' 632 'Paducah-Cape Girard-Harsbg' 633 'Odessa-Midland' 634 'Amarillo' 635 ' Austin' 636 'Harlingen-Wslco-Brnsvl-McA' 637 'Cedar Rapids-Wtrlo-IWC&Dub' 638 'St. Joseph' 639 'Jackson, TN' 640 'Memphis' 641 'San Antonio' 642 'Lafayette, LA' 643 'Lake Charles' 644 'Alexandria, LA' 647 'Greenwood-Greenville' 648 'Champaign&Sprngfld-Decatur' 649 'Evansville' 650 'Oklahoma City' 651 'Lubbock' 652 'Omaha' 656 'Panama City' 657 'Sherman-Ada' 658 'Green Bay-Appleton' 659 'Nashville' 661 'San Angelo' 662 'Abilene-Sweetwater' 669 'Madison' 670 'Ft. Smith-Fay-Sprngdl-Rgrs' 671 'Tulsa' 673 'Columbus-Tupelo-West Point' 675 'Peoria-Bloomington' 676 'Duluth-Superior' 678 'Wichita-Hutchinson Plus' 679 'Des Moines-Ames' 682 'Davenport-R.Island-Moline' 686 'Mobile-Pensacola (Ft Walt)' 687 'Minot-Bismarck-Dickinson' 691 'Huntsville-Decatur (Flor)' 692 'Beaumont-Port Arthur' 693 'Little Rock-Pine Bluff' 698 'Montgomery-Selma' 702 'La Crosse-Eau Claire' 705 'Wausau-Rhinelander' 709 'Tyler-Longview(Lfkn&Ncgd)' 710 'Hattiesburg-Laurel' 711 'Meridian' 716 'Baton Rouge' 717 'Quincy-Hannibal-Keokuk' 718 'Jackson, MS' 722 'Lincoln & Hastings-Krny' 724 'Fargo-Valley City' 725 'Sioux Falls(Mitchell)' 734 'Jonesboro' 736 'Bowling Green' 737 'Mankato' 740 'North Platte' 743 'Anchorage' 744 'Honolulu' 745 'Fairbanks' 746 'Biloxi-Gulfport' 747 'Juneau' 749 'Laredo' 751 'Denver' 752 'Colorado Springs-Pueblo' 753 'Phoenix (Prescott)' 754 'Butte-Bozeman' 755 'Great Falls' 756 'Billings' 757 'Boise' 758 'Idaho Falls-Pocatello' 759 'Cheyenne-Scottsbluff' 760 'Twin Falls' 762 'Missoula' 764 'Rapid City' 765 'El Paso (Las Cruces)' 766 'Helena' 767 'Casper-Riverton' 770 'Salt Lake City' 771 'Yuma-El Centro' 773 'Grand Junction-Montrose' 789 'Tucson (Sierra Vista)' 790 'Albuquerque-Santa Fe' 798 'Glendive' 800 'Bakersfield' 801 'Eugene' 802 'Eureka' 803 'Los Angeles' 804 'Palm Springs' 807 'San Francisco-Oak-San Jose' 810 'Yakima-Pasco-Rchlnd-Knnwck' 811 'Reno' 813 'Medford-Klamath Falls' 819 'Seattle-Tacoma' 820 'Portland, OR' 821 'Bend, OR' 825 'San Diego' 828 'Monterey-Salinas' 839 'Las Vegas' 855 'SantaBarbra-SanMar-SanLuOb' 862 'Sacramnto-Stkton-Modesto' 866 'Fresno-Visalia' 868 'Chico-Redding' 881 'Spokane' .
VALUE LABELS QtrN 51 'Y12Q3' 52 'Y12Q4' 53 'Y13Q1' 54 'Y13Q2' 55 'Y13Q3' 56 'Y13Q4' 57 'Y14Q1' .
EXECUTE .

SELECT IF (DmaN=803 or DmaN=501 or DmaN=623 or DmaN=807 or DmaN=602 or DmaN=618 or DmaN=528 or DmaN=511 or DmaN=524 or DmaN=504 or DmaN=641 or DmaN=506 or DmaN=505 or DmaN=825 or DmaN=753 or DmaN=751 or DmaN=862 or DmaN=534 or DmaN=839 or DmaN=616 or DmaN=819 or DmaN=613

or DmaN=609 or DmaN=512 or DmaN=535 or DmaN=820 or DmaN=539 or DmaN=517 or DmaN=527 or DmaN=515) .

RECODE DmaN (803=6) (501=7) (623=3) (807=9) (602=2) (618=5) (528=25) (511=10) (524=20) (504=8) (641=44) (506=1) (505=4) (825=31) (753=28)
(751=21) (862=42) (534=41) (839=24) (616=23) (819=32) (613=26) (609=33) (512=46) (535=38) (820=30) (539=45) (517=35) (527=22) (515=36) INTO MetroN .

VALUE LABELS MetroN 1 'Boston' 2 'Chicago' 3 'Dallas' 4 'Detroit' 5 'Houston' 6 'Los Angeles' 7 'New York' 8 'Philadelphia' 9 'San Francisco' 10 'Washington' 20 'Atlanta' 21 'Denver' 22 'Indianapolis' 23 'Kansas City' 24 'Las Vegas' 25 'Miami' 26 'Minneapolis' 27 'New Orleans' 28 'Phoenix' 29 'Pittsburgh' 30 'Portland' 31 'San Diego' 32 'Seattle' 33 'St Louis' 35 'Charlotte' 36 'Cincinnati' 37 'Cleveland' 38 'Columbus' 39 'Milwaukee' 40 'Norfolk' 41 'Orlando' 42 'Sacramento' 43 'Salt Lake City' 44 'San Antonio' 45 'Tampa' 46 'Baltimore' 47 'Austin' 48 'Rochester' 49 'Albany' 50 'Raleigh' 51 'Nashville' 52 'Greensboro' 53 'Buffalo' 54 'Daytona' 55 'Louisville' 56 'West Palm Beach' 57 'Memphis' 58 'Richmond' 59 'Providence' 60 'Grand Rapids' 61 'Tucson' 62 'Greenville' 63 'Syracuse' 64 'Birmingham' 65 'Omaha' 66 'Hartford' 67 'Toledo' 68 'Harrisburg' 69 'Knoxville' 70 'Honolulu' 71 'Albuquerque' 72 'Scranton' 73 'Youngstown' 74 'Colorado' 75 'Allentown' 76 'Fresno' 77 'Melbourne' 78 'Charleston' 79 'Dayton' 80 'Wichita' 81 'Columbia' 82 'Sarasota' 83 'Baton Rouge' 84 'Lansing' 85 'Springfield, MA' 86 'Lexington' 87 'Bakersfield' 88 'Fort Wayne' 89 'Spokane' 90 'Pensacola' 91 'Madison' 92 'Fort Myers' 93 'Boise' 94 'Augusta' 95 'Mobile' 96 'Other' 97 'Kalamazoo' 98 'Lakeland' 99 'Des Moines' 100 'Jacksonville' 101 'Chattanooga' 102 'Johnson City' 103 'El Paso' 104 'Stockton' 105 'Lancaster' 106 'Canton' 107 'Modesto' 108 'Saginaw Bay' 109 'Corpus Christi' 110 'Santa Barbara' 111 'Shreveport' 113 'Springfield, MO' 115 'Oklahoma City' 119 'Little Rock' .
SORT CASES BY QtrN(A) MetroN(A) CompanyN(A) .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Mec\MecGrp.sav' .

GET FILE 'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Mec\MecGrp.sav'.
IF (CompanyN=1) AttGrp=Grp1849 .
IF (CompanyN=2) VzGrp=Grp1849 .
IF (CompanyN=3) TmGrp=Grp1849 .
IF (CompanyN=4) SprGrp=Grp1849 .
IF (CompanyN=5) AppGrp=Grp1849 .
IF (CompanyN=6) SamGrp=Grp1849 .
IF (CompanyN=7) MotGrp=Grp1849 .
IF (CompanyN=8) HtcGrp=Grp1849 .

```
IF (CompanyN=9) LgGrp=Grp1849 .
IF (CompanyN=10) BbGrp=Grp1849 .
IF (CompanyN=11) NokGrp=Grp1849 .
IF (CompanyN=12) PansGrp=Grp1849 .
IF (CompanyN=13) PantGrp=Grp1849 .
IF (CompanyN=14) SonyGrp=Grp1849 .
EXECUTE .
AGGREGATE /OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Mec\MecGrpMerge.sav'
/BREAK=QtrN MetroN
/AttGrp=MEAN(AttGrp)
/VzGrp=MEAN(VzGrp)
/TmGrp=MEAN(TmGrp)
/SprGrp=MEAN(SprGrp)
/AppGrp=MEAN(AppGrp)
/SamGrp=MEAN(SamGrp)
/MotGrp=MEAN(MotGrp)
/HtcGrp=MEAN(HtcGrp)
/LgGrp=MEAN(LgGrp)
/BbGrp=MEAN(BbGrp)
/NokGrp=MEAN(NokGrp)
/PansGrp=MEAN(PansGrp)
/PantGrp=MEAN(PantGrp)
/SonyGrp=MEAN(SonyGrp) .
GET FILE
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Mec\MecGrpMerge.sav'.
SELECT IF (NOT SYSMIS(QtrN)) .
SORT CASES BY QtrN(A) MetroN(A) .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Mec\MecGrpMerge.sav' .
```

APPENDIX D

SPSS CODE FOR NEILSEN DATA READ AND AGGREGATE – FOUNDATION OR SMARTPHONE ONLY BLP

```
GET DATA /TYPE=XLSX /FILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Descriptives.xlsx'
  /SHEET=name 'Specs' /CELLRANGE=full /READNAMES=on
/ASSUMEDSTRWIDTH=32767 .
SORT CASES BY B1900(A) .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Features.sav'
/DROP=B1900Model URL /COMPRESSED .

GET FILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Neilsen\Jan\MP_Dataset.sav' .
SELECT IF (MONTH > 78 and MONTH < 92) .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Neilsen\Jan\Temp01.sav' .
GET FILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Neilsen\March\MP_Dataset.s
av' .
SELECT IF (MONTH > 91 and MONTH < 97) .
SAVE
OUTFILE='C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Neilsen\March\Te
mp02.sav' .

GET FILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Neilsen\Jan\Temp01.sav' .
ADD FILES /FILE=* /FILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Neilsen\March\Temp02.sav' .
COMPUTE MonthN=Month .
COMPUTE QtrN=WAVE_ID .
VALUE LABELS MonthN 79 'July 2012' 80 'Aug 2012' 81 'Sept 2012' 82 'Oct 2012' 83
'Nov 2012' 84 'Dec 2012'  85 'Jan 2013' 86 'Feb 2013' 87  'Mar 2013' 88 'Apr 2013' 89
'May 2013' 90 'Jun 2013' 91 'Jul 2013' 92 'Aug 2013' 93 'Sep 2013' 94 'Oct 2013' 95 'Nov
2013' 96 'Dec 2013' .
VALUE LABELS QtrN 51 'Y12Q3' 52 'Y12Q4' 53 'Y13Q1' 54 'Y13Q2' 55 'Y13Q3' 56
'Y13Q4' .
```

```
SORT CASES BY B1900(A) .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Neilsen\Neilen.sav' .
MATCH FILES /FILE=*
/TABLE='C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Features.sav' /BY
B1900.
EXECUTE .
RECODE B1900 (9104=1) (9103=2) (9105=3) (2326=4) (2288=5) (2371=6) (2349=7)
(9106=8) (132=9) (9232=10) (157=11) (3211=12) (149=13) (2300=14) (2311=15)
(9270=16) (9282=17) (2258=18) (2305=19) (2295=20) (9245=21) (2287=22) (129=23)
(3185=24) (759=25) (ELSE=0) INTO PhoneN .
RECODE B1900 (9104=5) (9103=5) (9105=5) (2326=6) (2288=6) (2371=6) (2349=6)
(9106=5) (132=7) (9232=8) (157=7) (3211=9) (149=7) (2300=6) (2311=6) (9270=8)
(9282=8) (2258=6) (2305=6) (2295=6) (9245=8) (2287=6) (129=7) (3185=9) (759=7)
(ELSE=0) INTO CompanyN .
VARIABLE LABELS CompanyN 'Company' PhoneN 'Phone Model' .
VALUE LABELS CompanyN 1 'AT&T' 2 'Verizon' 3 'T-Mobile' 4 'Sprint' 5 'Apple' 6
'Samsung' 7 'Motorola' 8 'HTC' 9 'LG' 10 'Blackberry' 11 'Nokia' 12 'Panasonic' 13
'Pantech' 14 'Sony' .
RECODE OS ('Andriod'=1) ('iOS'=2) ('Windows'=3) ('BlackBerry'=4) (ELSE=0) INTO
OS_n .
RECODE q157 (1=1) (2=2) (3=3) (4=4) (5=5) (6=6) (7=7) (8=8) (9=9) (10=10) (11=11)
(99=SYSMIS) INTO Income .
RECODE q103 (1=1) (2=0) (ELSE=SYSMIS) INTO Gender .
RECODE q135 (1=1) (2,3,4,5,6=0) (ELSE=SYSMIS) INTO Married .
RECODE B2520 (1=1) (2=0) (96=0) (ELSE=SYSMIS) INTO HomeOwner .
RECODE q210
(6,7,3,9,2,5,25,10,20,8,44,1,4,31,28,21,42,41,24,23,32,26,33,46,38,30,45,35,22,36=1)
INTO MetroSelect .
RECODE topprvd (1=1) (2=4) (3=3) (4=2) (5=5) INTO CarrierN .
COMPUTE MetroN=q210 .
COMPUTE PhonePrice=B485r .
COMPUTE Age=q106 .
COMPUTE CarrierPrice=Q455r .
COMPUTE ContractLength=q4102 .
COMPUTE HhSize=SUM(Adults,Kids) .
RECODE raceEthn (1=1) (ELSE=0) INTO EthHisp .
RECODE raceEthn (2=1) (ELSE=0) INTO EthWhite .
RECODE raceEthn (3=1) (ELSE=0) INTO EthBlk .
```

```
RECODE raceEthn (4=1) (ELSE=0) INTO EthAsian .
RECODE q103 (1=1) (2=0) INTO GenderMale .
RECODE q157 (99=SYSMIS) (ELSE=COPY) INTO Income .
RECODE EMPLOY (4=1) (ELSE=0) INTO Unempl .
RECODE B2520 (1=1) (ELSE=0) INTO Home .
RECODE KIDS (0=0) (1,2,3,4,5=1) INTO HaveKids .
RECODE q135 (1,6=1) (2,3,4,5=0) INTO Partner .
RECODE educ (1,2,3=0) (4,5=1) (ELSE=SYSMIS) INTO College .
RECODE plantype (1=1) (ELSE=0) INTO PlanCorp .
RECODE plantype (1=2) (ELSE=0) INTO PlanPreP .
RECODE plantype (1=3) (ELSE=0) INTO PlanInd .
RECODE plantype (1=4) (ELSE=0) INTO PlanFam .
IF (PhoneN=0) OS_n=0 .
EXECUTE .

VALUE LABELS PhoneN 0 'Other Phone' 1 'Apple iPhone 4S' 2 'Apple iPhone 4' 3
'Apple IPhone 5' 4 'Samsung Galaxy S III' 5 'Samsung Galaxy S II' 6 'Samsung Galaxy
S4' 7 'Samsung Galaxy Note II' 8 'Apple iPhone 5S' 9 'Motorola Droid RAZR' 10 'HTC
Evo 4G' 11 'Motorola Droid RAZR M' 12 'LG Motion 4G / Optimus Regard' 13
'Motorola Droid RAZR MAXX' 14 'Samsung Galaxy Nexus' 15 'Samsung Galaxy S
Blaze 4G' 16 'HTC Evo 4G LTE' 17 'HTC One' 18 'Samsung Galaxy S 4G' 19 'Samsung
Exhibit II 4G / Galaxy Exhibit 4G' 20 'Samsung Stratosphere' 21 'HTC Inspire 4G' 22
'Samsung Admire / Vitality' 23 'Motorola Droid Bionic' 24 'LG Lucid / Optimus Exceed'
25 'Motorola Droid X' .
VALUE LABELS OS_n 0 'Other' 1 'Android' 2 'iOS'  3 'Windows' 4 'BlackBerry' .
VALUE LABELS MetroN 1 'Boston' 2 'Chicago' 3 'Dallas' 4 'Detroit' 5 'Houston' 6 'Los
Angeles' 7 'New York' 8 'Philadelphia' 9 'San Francisco' 10 'Washington' 20 'Atlanta' 21
'Denver' 22 'Indianapolis' 23 'Kansas City' 24 'Las Vegas' 25 'Miami' 26 'Minneapolis' 27
'New Orleans' 28 'Phoenix' 29 'Pittsburgh' 30 'Portland' 31 'San Diego' 32 'Seattle' 33 'St
Louis' 35 'Charlotte' 36 'Cincinnati' 37 'Cleveland' 38 'Columbus' 39 'Milwaukee' 40
'Norfolk' 41 'Orlando' 42 'Sacramento' 43 'Salt Lake City' 44 'San Antonio' 45 'Tampa' 46
'Baltimore' 47 'Austin' 48 'Rochester' 49 'Albany' 50 'Raleigh' 51 'Nashville' 52
'Greensboro' 53 'Buffalo' 54 'Daytona' 55 'Louisville' 56 'West Palm Beach' 57 'Memphis'
58 'Richmond' 59 'Providence' 60 'Grand Rapids' 61 'Tucson' 62 'Greenville' 63 'Syracuse'
64 'Birmingham' 65 'Omaha' 66 'Hartford' 67 'Toledo' 68 'Harrisburg' 69 'Knoxville' 70
'Honolulu' 71 'Albuquerque' 72 'Scranton' 73 'Youngstown' 74 'Colorado' 75 'Allentown'
76 'Fresno' 77 'Melbourne' 78 'Charleston' 79 'Dayton' 80 'Wichita' 81 'Columbia' 82
'Sarasota' 83 'Baton Rouge' 84 'Lansing' 85 'Springfield, MA' 86 'Lexington' 87
'Bakersfield' 88 'Fort Wayne' 89 'Spokane' 90 'Pensacola' 91 'Madison' 92 'Fort Myers' 93
```

```
'Boise' 94 'Augusta' 95 'Mobile' 96 'Other' 97 'Kalamazoo' 98 'Lakeland' 99 'Des Moines'
100 'Jacksonville' 101 'Chattanooga' 102 'Johnson City' 103 'El Paso' 104 'Stockton' 105
'Lancaster' 106 'Canton' 107 'Modesto' 108 'Saginaw Bay' 109 'Corpus Christi' 110 'Santa
Barbara' 111 'Shreveport' 113 'Springfield, MO' 115 'Oklahoma City' 119 'Little Rock' .
VALUE LABELS CarrierN 1 'AT&T' 2 'Verizon' 3 'T-Mobile' 4 'Sprint' 5 'Other' .
IF (IntroDate >= DATE.DMY(1,1,2010) and IntroDate < DATE.DMY(1,2,2010))
IntroMonth = 49 .
IF (IntroDate >= DATE.DMY(1,2,2010) and IntroDate < DATE.DMY(1,3,2010))
IntroMonth = 50 .
IF (IntroDate >= DATE.DMY(1,3,2010) and IntroDate < DATE.DMY(1,4,2010))
IntroMonth = 51 .
IF (IntroDate >= DATE.DMY(1,4,2010) and IntroDate < DATE.DMY(1,5,2010))
IntroMonth = 52 .
IF (IntroDate >= DATE.DMY(1,5,2010) and IntroDate < DATE.DMY(1,6,2010))
IntroMonth = 53 .
IF (IntroDate >= DATE.DMY(1,6,2010) and IntroDate < DATE.DMY(1,7,2010))
IntroMonth = 54 .
IF (IntroDate >= DATE.DMY(1,7,2010) and IntroDate < DATE.DMY(1,8,2010))
IntroMonth = 55 .
IF (IntroDate >= DATE.DMY(1,8,2010) and IntroDate < DATE.DMY(1,9,2010))
IntroMonth = 56 .
IF (IntroDate >= DATE.DMY(1,9,2010) and IntroDate < DATE.DMY(1,10,2010))
IntroMonth = 57 .
IF (IntroDate >= DATE.DMY(1,10,2010) and IntroDate < DATE.DMY(1,11,2010))
IntroMonth = 58 .
IF (IntroDate >= DATE.DMY(1,11,2010) and IntroDate < DATE.DMY(1,12,2010))
IntroMonth = 59 .
IF (IntroDate >= DATE.DMY(1,12,2010) and IntroDate < DATE.DMY(1,1,2011))
IntroMonth = 60 .
IF (IntroDate >= DATE.DMY(1,1,2011) and IntroDate < DATE.DMY(1,2,2011))
IntroMonth = 61 .
IF (IntroDate >= DATE.DMY(1,2,2011) and IntroDate < DATE.DMY(1,3,2011))
IntroMonth = 62 .
IF (IntroDate >= DATE.DMY(1,3,2011) and IntroDate < DATE.DMY(1,4,2011))
IntroMonth = 63 .
IF (IntroDate >= DATE.DMY(1,4,2011) and IntroDate < DATE.DMY(1,5,2011))
IntroMonth = 64 .
IF (IntroDate >= DATE.DMY(1,5,2011) and IntroDate < DATE.DMY(1,6,2011))
IntroMonth = 65 .
```

```
IF (IntroDate >= DATE.DMY(1,6,2011) and IntroDate < DATE.DMY(1,7,2011))
IntroMonth = 66 .
IF (IntroDate >= DATE.DMY(1,7,2011) and IntroDate < DATE.DMY(1,8,2011))
IntroMonth = 67 .
IF (IntroDate >= DATE.DMY(1,8,2011) and IntroDate < DATE.DMY(1,9,2011))
IntroMonth = 68 .
IF (IntroDate >= DATE.DMY(1,9,2011) and IntroDate < DATE.DMY(1,10,2011))
IntroMonth = 69 .
IF (IntroDate >= DATE.DMY(1,10,2011) and IntroDate < DATE.DMY(1,11,2011))
IntroMonth = 70 .
IF (IntroDate >= DATE.DMY(1,11,2011) and IntroDate < DATE.DMY(1,12,2011))
IntroMonth = 71 .
IF (IntroDate >= DATE.DMY(1,12,2011) and IntroDate < DATE.DMY(1,1,2012))
IntroMonth = 72 .
IF (IntroDate >= DATE.DMY(1,1,2012) and IntroDate < DATE.DMY(1,2,2012))
IntroMonth = 73 .
IF (IntroDate >= DATE.DMY(1,2,2012) and IntroDate < DATE.DMY(1,3,2012))
IntroMonth = 74 .
IF (IntroDate >= DATE.DMY(1,3,2012) and IntroDate < DATE.DMY(1,4,2012))
IntroMonth = 75 .
IF (IntroDate >= DATE.DMY(1,4,2012) and IntroDate < DATE.DMY(1,5,2012))
IntroMonth = 76 .
IF (IntroDate >= DATE.DMY(1,5,2012) and IntroDate < DATE.DMY(1,6,2012))
IntroMonth = 77 .
IF (IntroDate >= DATE.DMY(1,6,2012) and IntroDate < DATE.DMY(1,7,2012))
IntroMonth = 78 .
IF (IntroDate >= DATE.DMY(1,7,2012) and IntroDate < DATE.DMY(1,8,2012))
IntroMonth = 79 .
IF (IntroDate >= DATE.DMY(1,8,2012) and IntroDate < DATE.DMY(1,9,2012))
IntroMonth = 80 .
IF (IntroDate >= DATE.DMY(1,9,2012) and IntroDate < DATE.DMY(1,10,2012))
IntroMonth = 81 .
IF (IntroDate >= DATE.DMY(1,10,2012) and IntroDate < DATE.DMY(1,11,2012))
IntroMonth = 82 .
IF (IntroDate >= DATE.DMY(1,11,2012) and IntroDate < DATE.DMY(1,12,2012))
IntroMonth = 83 .
IF (IntroDate >= DATE.DMY(1,12,2012) and IntroDate < DATE.DMY(1,1,2013))
IntroMonth = 84 .
```

```
IF (IntroDate >= DATE.DMY(1,1,2013) and IntroDate < DATE.DMY(1,2,2013))
IntroMonth = 85 .
IF (IntroDate >= DATE.DMY(1,2,2013) and IntroDate < DATE.DMY(1,3,2013))
IntroMonth = 86 .
IF (IntroDate >= DATE.DMY(1,3,2013) and IntroDate < DATE.DMY(1,4,2013))
IntroMonth = 87 .
IF (IntroDate >= DATE.DMY(1,4,2013) and IntroDate < DATE.DMY(1,5,2013))
IntroMonth = 88 .
IF (IntroDate >= DATE.DMY(1,5,2013) and IntroDate < DATE.DMY(1,6,2013))
IntroMonth = 89 .
IF (IntroDate >= DATE.DMY(1,6,2013) and IntroDate < DATE.DMY(1,7,2013))
IntroMonth = 90 .
IF (IntroDate >= DATE.DMY(1,7,2013) and IntroDate < DATE.DMY(1,8,2013))
IntroMonth = 91 .
IF (IntroDate >= DATE.DMY(1,8,2013) and IntroDate < DATE.DMY(1,9,2013))
IntroMonth = 92 .
IF (IntroDate >= DATE.DMY(1,9,2013) and IntroDate < DATE.DMY(1,10,2013))
IntroMonth = 93 .
IF (IntroDate >= DATE.DMY(1,10,2013) and IntroDate < DATE.DMY(1,11,2013))
IntroMonth = 94 .
IF (IntroDate >= DATE.DMY(1,11,2013) and IntroDate < DATE.DMY(1,12,2013))
IntroMonth = 95 .
IF (IntroDate >= DATE.DMY(1,12,2013) and IntroDate < DATE.DMY(1,1,2014))
IntroMonth = 96 .
* MONTH 95=Nov2013 .
COMPUTE PhoneAge=Month-IntroMonth .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Neilsen\WirelessData.sav .

* Aggregate .
GET FILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Neilsen\WirelessData.sav' .
USE ALL.
SELECT IF (MetroSelect=1) .
EXECUTE.

RECODE CarrierN (1=1) (ELSE=0) INTO CarAtt .
RECODE CarrierN (2=1) (ELSE=0) INTO CarVz .
RECODE CarrierN (3=1) (ELSE=0) INTO CarTm .
```

```
RECODE CarrierN (4=1) (ELSE=0) INTO CarSpr .
RECODE CarrierN (5=1) (ELSE=0) INTO CarOth .
EXECUTE .
IF (CarAtt=1) PriceAtt=CarrierPrice .
IF (CarVz=1) PriceVz=CarrierPrice .
IF (CarTm=1) PriceTm=CarrierPrice .
IF (CarSpr=1) PriceSpr=CarrierPrice .
IF (CarOth=1) PriceOth=CarrierPrice .
COMPUTE PhoneCount=1 .
EXECUTE .

USE ALL .
SORT CASES BY QtrN MetroN PhoneN .

AGGREGATE /OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Neilsen\NeilsenAgg.sav'
/BREAK=QtrN MetroN PhoneN
/CompanyN=FIRST(CompanyN)
/PhonePrice=MEAN(PhonePrice)
/ScreenSize=FIRST(ScreenSize)
/Weight=FIRST(Weight)
/TalkTime=FIRST(TalkTime)
/OS_n=FIRST(OS_n)
/KeyBoard=FIRST(KeyBoard)
/ContractLength=MEAN(ContractLength)
/PhoneAge=MEAN(PhoneAge)
/CarrierPrice=MEAN(CarrierPrice)
/College=MEAN(College)
/PlanCorp=MEAN(PlanCorp)
/PlanPreP=MEAN(PlanPreP)
/PlanInd=MEAN(PlanInd)
/PlanFam=MEAN(PlanFam)
/PrePaid=MEAN(prepaid)
/Promo=MEAN(Promo)
/Income=MEAN(Income)
/Age=MEAN(Age)
/EthHisp=MEAN(EthHisp)
/EthWhite=MEAN(EthWhite)
/EthBlk=MEAN(EthBlk)
```

```
/EthAsian=MEAN(EthAsian)
/GenderMale=MEAN(GenderMale)
/Unempl=MEAN(Unempl)
/Home=MEAN(Home)
/HaveKids=MEAN(HaveKids)
/Partner=MEAN(Partner)
/Adults=MEAN(Adults)
/Kids=MEAN(Kids)
/HhSize=MEAN(HhSize)
/CarAtt=MEAN(CarAtt)
/CarVz=MEAN(CarVz)
/CarTm=MEAN(CarTm)
/CarSpr=MEAN(CarSpr)
/CarOth=MEAN(CarOth)
/PriceAtt=MEAN(PriceAtt)
/PriceVz=MEAN(PriceVz)
/PriceTm=MEAN(PriceTm)
/PriceSpr=MEAN(PriceSpr)
/PriceOth=MEAN(PriceOth)
/PhoneSum=SUM(PhoneCount) .
GET FILE
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Neilsen\NeilsenAgg.sav' .
RECODE PhoneAge (-999 THRU 0=0) (ELSE=COPY) .
EXECUTE .
AGGREGATE /OUTFILE=* MODE=ADDVARIABLES /BREAK=QtrN MetroN
/PhoneSum2=SUM(PhoneSum).
COMPUTE PhoneShare=PhoneSum/PhoneSum2 .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Neilsen\NeilsenAgg.sav' .
```

APPENDIX E

SPSS CODE USED TO CREATE MIXED LOGIT DATA

```
GET FILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Neilsen\WirelessData.sav' .
USE ALL.
SELECT IF (IntroDate >= DATE.DMY(1,1,2010) and ScreenSize>=3.5 and
MetroSelect=1 and PrePaid=0) .
EXECUTE.

RECODE CarrierN (1=1) (ELSE=0) INTO CarAtt .
RECODE CarrierN (2=1) (ELSE=0) INTO CarVz .
RECODE CarrierN (3=1) (ELSE=0) INTO CarTm .
RECODE CarrierN (4=1) (ELSE=0) INTO CarSpr .
RECODE CarrierN (5=1) (ELSE=0) INTO CarOth .
RECODE PhoneAge (-999 THRU 0=0) (ELSE=COPY) .
EXECUTE .

SORT CASES BY QtrN(A) MetroN(A) .

* Matching MEC to Neilsen .
MATCH FILES /FILE=* /TABLE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Mec\MecGrpMerge.sav'
/BY QtrN MetroN .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\RepData.sav' .
GET FILE 'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\RepData.sav' .

* Match above to Social .
SORT CASES BY QtrN(A) .
SAVE
OUTFILE='C:\Users\Michael\Documents\Personal\PhD\Michael\Data\RepData.sav' .
MATCH FILES /FILE=* /TABLE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Social\Social.sav'
/BY QtrN .
SAVE
OUTFILE='C:\Users\Michael\Documents\Personal\PhD\Michael\Data\RepData.sav'
/KEEP=merge_id MonthN QtrN MetroN PhoneN CarrierN CompanyN ScreenSize
Weight TalkTime KeyBoard OS_n PhonePrice CarrierPrice ContractLength Promo
```

IntroMonth PhoneAge CarAtt CarVz CarTm CarSpr CarOth Income Gender Married Age EthHisp EthWhite EthBlk EthAsian GenderMale Unempl Home HaveKids Adults Kids HhSize Partner College AttGrp VzGrp TmGrp SprGrp AppGrp SamGrp MotGrp HtcGrp LgGrp BbGrp NokGrp PansGrp PantGrp SonyGrp AttNeu AttPos AttNeg VzNeu VzPos VzNeg SprNeu SprPos SprNeg TmNeu TmPos TmNeg .

APPENDIX F

SAS CODE USED TO RANDOMLY SELECT UNOBSERVED PRICES

```
libname Phd "C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Matlab\Logit\";

proc import out=test
datafile= "C:\Users\Michael\Documents\Personal\PhD\Michael\Data\RepData.sav"
dbms=SPSS REPLACE;
run;

data Phd.RepData; set test; run;

data one; set Phd.RepData(rename=(Weight=Wgt));
if Income ne .;
if Age ne .;
if HhSize ne .;
run;

data oneA; set one(keep=QtrN MetroN PhoneN PhonePrice TalkTime ScreenSize Wgt);
if PhonePrice ne .; run;
proc means data=oneA noprint; by QtrN MetroN PhoneN; var PhonePrice TalkTime
ScreenSize Wgt;
output out=two(DROP=_TYPE_ _FREQ_) MEAN=PhonePriceM TalkTime ScreenSize
Wgt; run;

data oneB; set one(rename=(PhonePrice=PhonePriceC PhoneN=PhoneNc)
drop=TalkTime ScreenSize Wgt OS_n Keyboard);
if PhonePriceC ne .; run;
data oneB; set oneB;
rep_id=_N_; run;

*Adding unobserved choices;
proc sql;
create table thr as
select oneB.*, two.PhoneN
from oneB natural join two;
quit;
proc sort data=thr; by rep_id; run;

proc sort data=two; by QtrN MetroN PhoneN;
proc sort data=thr; by QtrN MetroN PhoneN;
data fou; merge thr two; by QtrN MetroN PhoneN;
  if PhoneN=PhoneNc then Choice=1; else Choice=0;
```

```
  if Choice=1 then PhonePrice=PhonePriceC; run;
proc sort data=fou; by rep_id; run;

* Adding missing prices;
data final; set fou; run;
data finalA; set final(keep=QtrN PhoneN PhonePrice where=(PhonePrice ne .));
proc sort; by QtrN PhoneN PhonePrice; run;

proc sql;
create table P_D_CNTS as
select QtrN,
PhoneN,
count(PhonePrice) as count
from finalA group by QtrN, PhoneN;
quit;

proc sql;
create table PD2 as select pd.QtrN, pd.PhoneN, pd.PhonePrice, cnts.count
from   finalA pd, P_D_CNTS cnts
where  pd.QtrN = cnts.QtrN
and  pd.PhoneN = cnts.PhoneN;
quit;

data PD3; set Pd2;
by QtrN PhoneN PhonePrice;
retain lower upper 0;
if first.PhoneN then do;
lower = 0;
upper = 1/count;
end;
else do;
lower = lower + 1/count;
upper = upper + 1/count;
end;
run;

data fiv; set fou; /*was final*/
random=rand('uniform');
run;

proc sql;
create table final as
select fiv.rep_id, fiv.QtrN, fiv.MetroN, fiv.PhoneN, fiv.PhonePrice, fiv.Choice,
fiv.ScreenSize, fiv.TalkTime,
```

```
fiv.Wgt, fiv.Age, fiv.HhSize, fiv.Income
from fiv
where  PhonePrice ne .
union
select fiv.rep_id, fiv.QtrN, fiv.MetroN, fiv.PhoneN, PD3.PhonePrice, fiv.Choice,
fiv.ScreenSize, fiv.TalkTime,
fiv.Wgt, fiv.Age, fiv.HhSize, fiv.Income
from   fiv,
PD3
where  fiv.QtrN = PD3.QtrN
and fiv.PhoneN = pd3.PhoneN
and fiv.random between pd3.lower and pd3.upper
and fiv.PhonePrice eq .;
quit;

data final; set final;
situation=rep_id; run;
proc print data=final(obs=1000);var Rep_id situation Choice PhonePrice ScreenSize
TalkTime Wgt Age HhSize Income QtrN MetroN PhoneN; run;
proc sort data=final; by Choice PhoneN; run;
proc means data=final noprint; by Choice PhoneN; var PhonePrice;
output out=ppout(DROP=_TYPE_ _FREQ_) MEAN=PhonePriceM STD=PhonePrieS
N=PhoneCount MIN=PhonePriceMin MAX=PhonePriceMax; run;
proc print data=ppout; run;

* File or SAS Mixed Model;
proc sort data=final; by rep_id PhoneN; run;
libname Mix
"C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Matlab\Logit\Sas\";
* removes problem formats;
data test; set final; run;
proc datasets lib=work memtype=data;
modify test;
attrib _all_ label=' ';
attrib _all_ format=;
run;
proc contents data=test; run;
data Mix.Mixed; set test; run;
```

APPENDIX G

SPSS CODE USED TO CREATE TRADITIONAL OR SMARTPHONE ONLY BLP DATA

```
GET FILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Neilsen\NeilsenAgg.sav'.
SELECT IF (NOT PhoneN=0) .
SORT CASES BY QtrN(A) MetroN(A) .
EXECUTE .

* Matching MEC to Neilsen .
MATCH FILES /FILE=* /TABLE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Mec\MecGrpMerge.sav'
/BY QtrN MetroN .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpData.sav' .

GET FILE 'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpData.sav' .

* Match Above to Social .
SORT CASES BY QtrN(A) .
SAVE
OUTFILE='C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpData.sav' .
MATCH FILES /FILE=*
/TABLE='C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Social\Social.sav'
/BY QtrN .
SAVE
OUTFILE='C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpData.sav' .

* PhoneCost .
GET DATA /TYPE=XLSX /FILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpPhoneCost.xlsx'
/SHEET=name 'Data' /CELLRANGE=range 'A1:B26' /READNAMES=on
/ASSUMEDSTRWIDTH=32767.
SORT CASES BY PhoneN(A) .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpPhoneCost.sav' .

GET FILE 'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpData.sav' .
```

```
SORT CASES BY PhoneN(A) .
MATCH FILES /FILE=*
/TABLE='C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpPhoneCost.sav'
/BY PhoneN .
SORT CASES BY QtrN(A) MetroN(A) .
SAVE
OUTFILE='C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpData.sav' .

* Adding External IV .
GET FILE 'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpData.sav' .
SORT CASES BY QtrN(A) MetroN(A) .
GET FILE 'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\IV\IV.sav' .
SORT CASES BY QtrN(A) MetroN(A) .
GET FILE 'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpData.sav' .
MATCH FILES /FILE=*
/TABLE='C:\Users\Michael\Documents\Personal\PhD\Michael\Data\IV\IV.sav'
  /BY QtrN MetroN .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpData.sav' .

GET FILE 'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpData.sav' .
SELECT IF (NOT MISS(PhonePrice)) .
SELECT IF (NOT MISS(CarrierPrice)) .
SELECT IF (NOT MISS(PhoneN)) .
SELECT IF (NOT PhoneN=0) .
SELECT IF (NOT MISS(ScreenSize)) .
SELECT IF (NOT MISS(TalkTime)) .
SELECT IF (NOT MISS(Weight)) .
SELECT IF (NOT MISS(ContractLength)) .
SELECT IF (NOT MISS(PhoneAge)) .
EXECUTE .

* Adding BLP Index Variables .
STRING id (A7) .
COMPUTE
id=CONCAT("1",STRING(PhoneN,N2),STRING(MetroN,N2),STRING(QtrN,N2)) .
EXECUTE .

IF ($casenum = 1) cdid=1 .
```

```
DO IF (LAG(MetroN)=MetroN) .
COMPUTE cdid=LAG(cdid) .
ELSE .
COMPUTE cdid=LAG(cdid) +1 .
END IF .
EXECUTE .

* Adding BLP Brand Dummy Variables .

RECODE PhoneN (1=1) (ELSE=0) INTO d_i4s.
RECODE PhoneN (2=1) (ELSE=0) INTO d_i4 .
RECODE PhoneN (3=1) (ELSE=0) INTO d_i5 .
RECODE PhoneN (4=1) (ELSE=0) INTO d_s3 .
RECODE PhoneN (5=1) (ELSE=0) INTO d_s2 .
RECODE PhoneN (6=1) (ELSE=0) INTO d_s4 .
RECODE PhoneN (7=1) (ELSE=0) INTO d_sn2 .
RECODE PhoneN (8=1) (ELSE=0) INTO d_i5s .
RECODE PhoneN (9=1) (ELSE=0) INTO d_mdr .
RECODE PhoneN (10=1) (ELSE=0) INTO d_he4g .
RECODE PhoneN (11=1) (ELSE=0) INTO d_mdrm .
RECODE PhoneN (12=1) (ELSE=0) INTO d_lgm .
RECODE PhoneN (13=1) (ELSE=0) INTO d_mdrx .
RECODE PhoneN (14=1) (ELSE=0) INTO d_snex .
RECODE PhoneN (15=1) (ELSE=0) INTO d_sbz .
RECODE PhoneN (16=1) (ELSE=0) INTO d_he4lte .
RECODE PhoneN (17=1) (ELSE=0) INTO d_ih1 .
RECODE PhoneN (18=1) (ELSE=0) INTO d_sgs .
RECODE PhoneN (19=1) (ELSE=0) INTO d_se4g .
RECODE PhoneN (20=1) (ELSE=0) INTO d_sstr .
RECODE PhoneN (21=1) (ELSE=0) INTO d_hins .
RECODE PhoneN (22=1) (ELSE=0) INTO d_sadm .
RECODE PhoneN (23=1) (ELSE=0) INTO d_mdb .
RECODE PhoneN (24=1) (ELSE=0) INTO d_lgl .
RECODE PhoneN (25=1) (ELSE=0) INTO d_mdx .
RECODE AttGrp VzGrp TmGrp SprGrp AppGrp SamGrp MotGrp HtcGrp LgGrp
BbGrp NokGrp PansGrp PantGrp SonyGrp (SYSMIS=0) .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpData.sav' /KEEP id cdid
QtrN MetroN PhoneN CompanyN PhonePrice ScreenSize Weight TalkTime PhoneShare
```

```
PhoneCost ContractLength PhoneAge CarrierPrice AttGrp VzGrp TmGrp SprGrp
AppGrp SamGrp MotGrp HtcGrp LgGrp BbGrp NokGrp PansGrp PantGrp SonyGrp
AttNeu AttPos AttNeg VzNeu VzPos VzNeg SprNeu SprPos SprNeg TmNeu TmPos
TmNeg ForceCnt EmployCnt UnemplCnt UE_Rate WirelessTelcom CopperWire
Electrometallurgical Transportation Warehouse Wireless372 Retail58 InorganicChem
SpecialMetels Copper19011 Plastics d_i4s d_i4 d_i5 d_s3 d_s2 d_s4 d_sn2 d_i5s d_mdr
d_he4g d_mdrm d_lgm d_mdrx d_snex d_sbz d_he4lte d_ih1 d_sgs d_se4g d_sstr
 d_hins d_sadm d_mdb d_lgl d_mdx .

*Creating excel file for imput into MatLab .
GET FILE 'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpData.sav' .
SAVE TRANSLATE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\MatLab\Blp\BlpDataNew.xls
x' /TYPE=XLS /VERSION=12 /MAP /REPLACE /FIELDNAMES /CELLS=VALUES .
```

APPENDIX H

SPSS CODE USED TO CREATE TRADITIONAL OR SMARTPHONE ONLY BLP DEMOGRAPHIC DRAWS DATA

```
* Must run RepNelCode first .
* Population Draw .
GET FILE 'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\RepData.sav' .
SELECT IF (NOT MISS(Income) ) .
COMPUTE RandomDraw=RV.UNIFORM(0,1).
EXECUTE.
SORT CASES BY QtrN(A) MetroN(A) RandomDraw(A) .
EXECUTE .

* Need to code the first Obs OrderN to 1 .
IF ($CASENUM=1) OrderN=1 .
IF (MetroN NE LAG(MetroN)) OrderN=1 .
EXECUTE .
IF (LAG(OrderN)=1) OrderN=2 .
IF (LAG(OrderN)=2) OrderN=3 .
IF (LAG(OrderN)=3) OrderN=4 .
IF (LAG(OrderN)=4) OrderN=5 .
IF (LAG(OrderN)=5) OrderN=6 .
IF (LAG(OrderN)=6) OrderN=7 .
IF (LAG(OrderN)=7) OrderN=8 .
IF (LAG(OrderN)=8) OrderN=9 .
IF (LAG(OrderN)=9) OrderN=10 .
IF (LAG(OrderN)=10) OrderN=11 .
IF (LAG(OrderN)=11) OrderN=12 .
IF (LAG(OrderN)=12) OrderN=13 .
IF (LAG(OrderN)=13) OrderN=14 .
IF (LAG(OrderN)=14) OrderN=15 .
IF (LAG(OrderN)=15) OrderN=16 .
IF (LAG(OrderN)=16) OrderN=17 .
IF (LAG(OrderN)=17) OrderN=18 .
IF (LAG(OrderN)=18) OrderN=19 .
IF (LAG(OrderN)=19) OrderN=20 .
EXECUTE .
FREQUENCIES VARIABLES=OrderN /ORDER=ANALYSIS .
SELECT IF (NOT MISS(OrderN)) .
```

```
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpPopDraw.sav'
/KEEP=QtrN MetroN OrderN Income Age HaveKids Partner College Married Home
EthHisp EthWhite EthBlk EthAsian GenderMale Unempl Home Adults Kids HhSize
College .

GET FILE 'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpPopDraw.sav' .
SORT CASES BY QtrN(A) MetroN(A) .
CASESTOVARS /ID=QtrN MetroN /INDEX=OrderN /GROUPBY=VARIABLE.
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpPopDraws.sav' .

* Price and attribute Draws .
GET FILE 'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\RepData.sav' .
SELECT IF (NOT MISS(PhonePrice) ) .
COMPUTE RandomDraw=RV.UNIFORM(0,1).
EXECUTE.
SORT CASES BY QtrN(A) MetroN(A) RandomDraw(A) .
EXECUTE .

* Need to code the first Obs OrderN to 1 .
IF ($CASENUM=1) OrderN=1 .
IF (MetroN NE LAG(MetroN)) OrderN=1 .
EXECUTE .
IF (LAG(OrderN)=1) OrderN=2 .
IF (LAG(OrderN)=2) OrderN=3 .
IF (LAG(OrderN)=3) OrderN=4 .
IF (LAG(OrderN)=4) OrderN=5 .
IF (LAG(OrderN)=5) OrderN=6 .
IF (LAG(OrderN)=6) OrderN=7 .
IF (LAG(OrderN)=7) OrderN=8 .
IF (LAG(OrderN)=8) OrderN=9 .
IF (LAG(OrderN)=9) OrderN=10 .
IF (LAG(OrderN)=10) OrderN=11 .
IF (LAG(OrderN)=11) OrderN=12 .
IF (LAG(OrderN)=12) OrderN=13 .
IF (LAG(OrderN)=13) OrderN=14 .
IF (LAG(OrderN)=14) OrderN=15 .
IF (LAG(OrderN)=15) OrderN=16 .
```

```
IF (LAG(OrderN)=16) OrderN=17 .
IF (LAG(OrderN)=17) OrderN=18 .
IF (LAG(OrderN)=18) OrderN=19 .
IF (LAG(OrderN)=19) OrderN=20 .
EXECUTE .
FREQUENCIES VARIABLES=OrderN /ORDER=ANALYSIS .
SELECT IF (NOT MISS(OrderN)) .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpVDraw.sav' /KEEP=QtrN
MetroN OrderN PhonePrice ScreenSize Weight TalkTime .
GET FILE 'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpVDraw.sav' .
SORT CASES BY QtrN(A) MetroN(A) .
CASESTOVARS /ID=QtrN MetroN /INDEX=OrderN /GROUPBY=VARIABLE.
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpVDraws.sav' .
```

APPENDIX I

SPSS CODE USED TO CREATE THE COMPLEMENT BLP DATA

```
GET FILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Neilsen\NeilsenAggCarReg.s
av'.
SELECT IF (NOT PhoneN=0) .
SORT CASES BY QtrN(A) RegionN(A) .
EXECUTE .

* Matching MEC to Neilsen .
GET FILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Mec\MecGrpMerge.sav' .
RECODE MetroN (1,7,10,8,46=1) (20,25,35,41,45=2) (4,2,22,26,36,38=3)
(3,5,23,33,44,21,28=4) (6,9,24,30,31,32,42=5) INTO RegionN .
VALUE LABELS RegionN 1 'NE' 2 'SE' 3 'MW' 4 'SW' 5 'W' .
AGGREGATE /OUTFILE  =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Mec\MecGrpMergeReg.sav'
/BREAK=QtrN RegionN /AttGrp=SUM(AttGrp) /VzGrp=SUM(VzGrp)
/TmGrp=SUM(TmGrp)  /SprGrp=SUM(SprGrp) /AppGrp=SUM(AppGrp)
/SamGrp=SUM(SamGrp)  /MotGrp=SUM(MotGrp) /HtcGrp=SUM(HtcGrp)
/LgGrp=SUM(LgGrp) /BbGrp=SUM(BbGrp) /NokGrp=SUM(NokGrp)
/PansGrp=SUM(PansGrp) /PantGrp=SUM(PantGrp) /SonyGrp=SUM(SonyGrp) .
EXECUTE .
GET FILE
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Neilsen\NeilsenAggCarReg.s
av' .
MATCH FILES /FILE=* /TABLE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Mec\MecGrpMergeReg.sav'
/BY QtrN RegionN .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpDataCarReg.sav' .
GET FILE
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpDataCarReg.sav' .

* Match Above to Social .
SORT CASES BY QtrN(A) .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpDataCarReg.sav' .
```

```
MATCH FILES /FILE=*
/TABLE='C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Social\Social.sav'
/BY QtrN .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpDataCarReg.sav' .

* PhoneCost .
GET DATA /TYPE=XLSX /FILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpPhoneCost.xlsx'
/SHEET=name 'Data' /CELLRANGE=range 'A1:B26' /READNAMES=on
/ASSUMEDSTRWIDTH=32767.
OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpPhoneCost.sav' .

GET FILE
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpDataCarReg.sav' .
SORT CASES BY PhoneN(A) .
MATCH FILES /FILE=*
/TABLE='C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpPhoneCost.sav'
/BY PhoneN .
SORT CASES BY QtrN(A) RegionN(A) .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpDataCarReg.sav' .

* Adding External IV .
GET FILE
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpDataCarReg.sav' .
SORT CASES BY QtrN(A) RegionN(A) .
GET FILE 'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\IV\IV.sav' .
RECODE MetroN (1,7,10,8,46=1) (20,25,35,41,45=2) (4,2,22,26,36,38=3)
(3,5,23,33,44,21,28=4) (6,9,24,30,31,32,42=5) INTO RegionN .
VALUE LABELS RegionN 1 'NE' 2 'SE' 3 'MW' 4 'SW' 5 'W' .
SORT CASES BY QtrN(A) RegionN(A) .
AGGREGATE
/OUTFILE='C:\Users\Michael\Documents\Personal\PhD\Michael\Data\IV\IVReg.sav'
/BREAK=QtrN RegionN /ForceCnt=SUM(ForceCnt)  /EmployCnt=SUM(EmployCnt)
/UnemplCnt=SUM(UnemplCnt)  /UE_Rate=MEAN(UE_Rate)
/WirelessTelcom=FIRST(WirelessTelcom)  /CopperWire=FIRST(CopperWire)
/Electrometallurgical=FIRST(Electrometallurgical)
```

```
/Transportation=FIRST(Transportation) /Warehouse=FIRST(Warehouse)
/Wireless372=FIRST(Wireless372) /Retail58=FIRST(Retail58)
/InorganicChem=FIRST(InorganicChem) /SpecialMetels=FIRST(SpecialMetels)
/Copper19011=FIRST(Copper19011)  /Plastics=FIRST(Plastics) .

GET FILE
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpDataCarReg.sav' .
MATCH FILES /FILE=* /TABLE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\IV\IVReg.sav'
/BY QtrN RegionN .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpDataCarReg.sav' .
GET FILE
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpDataCarReg.sav' .
SELECT IF (NOT MISS(PhonePrice)) .
SELECT IF (NOT MISS(CarrierPrice)) .
SELECT IF (NOT MISS(PhoneN)) .
SELECT IF (NOT MISS(CarrierN)) .
SELECT IF (NOT PhoneN=0) .
SELECT IF (NOT CarrierN=5) .
SELECT IF (NOT MISS(ScreenSize)) .
SELECT IF (NOT MISS(TalkTime)) .
SELECT IF (NOT MISS(Weight)) .
SORT CASES BY PhoneN(A) CarrierN(A) QtrN(A) RegionN(A) .
SAVE
OUTFILE='C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpDataCarReg.s
av' .

* Adding Index Variables .
GET FILE
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpDataCarReg.sav' .
STRING id_temp (A8) .
COMPUTE id_temp=CONCAT("1",STRING(PhoneN,N2), STRING(CarrierN,N2),
STRING(RegionN,N2),STRING(QtrN,N2)) .
EXECUTE .
COMPUTE id = number(id_temp, F8).
EXECUTE .
SORT CASES BY QtrN(A) RegionN(A) .
EXECUTE .
```

```
IF ($casenum = 1) cdid=1 .
DO IF (LAG(RegionN)=RegionN) .
COMPUTE cdid=LAG(cdid) .
ELSE .
COMPUTE cdid=LAG(cdid) +1 .
END IF .
EXECUTE .

*Adding Brand Dummies .
IF (PhoneN=1 and CarrierN=1) d_i4s_att=1 .
IF (PhoneN=1 and CarrierN=2) d_i4s_vz=1 .
IF (PhoneN=1 and CarrierN=3) d_i4s_tm=1 .
IF (PhoneN=1 and CarrierN=4) d_i4s_spr=1 .
IF (PhoneN=2 and CarrierN=1) d_i4_att=1 .
IF (PhoneN=2 and CarrierN=2) d_i4_vz=1 .
IF (PhoneN=2 and CarrierN=3) d_i4_tm=1 .
IF (PhoneN=2 and CarrierN=4) d_i4_spr=1 .
IF (PhoneN=3 and CarrierN=1) d_i5_att=1 .
IF (PhoneN=3 and CarrierN=2) d_i5_vz=1 .
IF (PhoneN=3 and CarrierN=3) d_i5_tm=1 .
IF (PhoneN=3 and CarrierN=4) d_i5_spr=1 .
IF (PhoneN=4 and CarrierN=1) d_s3_att=1 .
IF (PhoneN=4 and CarrierN=2) d_s3_vz=1 .
IF (PhoneN=4 and CarrierN=3) d_s3_tm=1 .
IF (PhoneN=4 and CarrierN=4) d_s3_spr=1 .
IF (PhoneN=5 and CarrierN=1) d_s2_att=1 .
IF (PhoneN=5 and CarrierN=2) d_s2_vz=1 .
IF (PhoneN=5 and CarrierN=3) d_s2_tm=1 .
IF (PhoneN=5 and CarrierN=4) d_s2_spr=1 .
IF (PhoneN=6 and CarrierN=1) d_s4_att=1 .
IF (PhoneN=6 and CarrierN=2) d_s4_vz=1 .
IF (PhoneN=6 and CarrierN=3) d_s4_tm=1 .
IF (PhoneN=6 and CarrierN=4) d_s4_spr=1 .
IF (PhoneN=7 and CarrierN=1) d_sn2_att=1 .
IF (PhoneN=7 and CarrierN=2) d_sn2_vz=1 .
IF (PhoneN=7 and CarrierN=3) d_sn2_tm=1 .
IF (PhoneN=7 and CarrierN=4) d_sn2_spr=1 .
IF (PhoneN=8 and CarrierN=1) d_i5s_att=1 .
IF (PhoneN=8 and CarrierN=2) d_i5s_vz=1 .
```

IF (PhoneN=8 and CarrierN=3) d_i5s_tm=1 .
IF (PhoneN=8 and CarrierN=4) d_i5s_spr=1 .
IF (PhoneN=9 and CarrierN=1) d_mdr_att=1 .
IF (PhoneN=9 and CarrierN=2) d_mdr_vz=1 .
IF (PhoneN=9 and CarrierN=3) d_mdr_tm=1 .
IF (PhoneN=9 and CarrierN=4) d_mdr_spr=1 .
IF (PhoneN=10 and CarrierN=1) d_he4_att=1 .
IF (PhoneN=10 and CarrierN=2) d_he4_vz=1 .
IF (PhoneN=10 and CarrierN=3) d_he4_tm=1 .
IF (PhoneN=10 and CarrierN=4) d_he4_spr=1 .
IF (PhoneN=11 and CarrierN=1) d_mdrm_att=1 .
IF (PhoneN=11 and CarrierN=2) d_mdrm_vz=1 .
IF (PhoneN=11 and CarrierN=3) d_mdrm_tm=1 .
IF (PhoneN=11 and CarrierN=4) d_mdrm_spr=1 .
IF (PhoneN=12 and CarrierN=1) d_lm4_att=1 .
IF (PhoneN=12 and CarrierN=2) d_lm4_vz=1 .
IF (PhoneN=12 and CarrierN=3) d_lm4_tm=1 .
IF (PhoneN=12 and CarrierN=4) d_lm4_spr=1 .
IF (PhoneN=13 and CarrierN=1) d_mdrx_att=1 .
IF (PhoneN=13 and CarrierN=2) d_mdrx_vz=1 .
IF (PhoneN=13 and CarrierN=3) d_mdrx_tm=1 .
IF (PhoneN=13 and CarrierN=4) d_mdrx_spr=1 .
IF (PhoneN=14 and CarrierN=1) d_sns_att=1 .
IF (PhoneN=14 and CarrierN=2) d_sns_vz=1 .
IF (PhoneN=14 and CarrierN=3) d_sns_tm=1 .
IF (PhoneN=14 and CarrierN=4) d_sns_spr=1 .
IF (PhoneN=15 and CarrierN=1) d_sbl_att=1 .
IF (PhoneN=15 and CarrierN=2) d_sbl_vz=1 .
IF (PhoneN=15 and CarrierN=3) d_sbl_tm=1 .
IF (PhoneN=15 and CarrierN=4) d_sbl_spr=1 .
IF (PhoneN=16 and CarrierN=1) d_hel_att=1 .
IF (PhoneN=16 and CarrierN=2) d_hel_vz=1 .
IF (PhoneN=16 and CarrierN=3) d_hel_tm=1 .
IF (PhoneN=16 and CarrierN=4) d_hel_spr=1 .
IF (PhoneN=17 and CarrierN=1) d_ho_att=1 .
IF (PhoneN=17 and CarrierN=2) d_ho_vz=1 .
IF (PhoneN=17 and CarrierN=3) d_ho_tm=1 .
IF (PhoneN=17 and CarrierN=4) d_ho_spr=1 .
IF (PhoneN=18 and CarrierN=1) d_ss_att=1 .

```
IF (PhoneN=18 and CarrierN=2) d_ss_vz=1 .
IF (PhoneN=18 and CarrierN=3) d_ss_tm=1 .
IF (PhoneN=18 and CarrierN=4) d_ss_spr=1 .
IF (PhoneN=19 and CarrierN=1) d_se_att=1 .
IF (PhoneN=19 and CarrierN=2) d_se_vz=1 .
IF (PhoneN=19 and CarrierN=3) d_se_tm=1 .
IF (PhoneN=19 and CarrierN=4) d_se_spr=1 .
IF (PhoneN=20 and CarrierN=1) d_sst_att=1 .
IF (PhoneN=20 and CarrierN=2) d_sst_vz=1 .
IF (PhoneN=20 and CarrierN=3) d_sst_tm=1 .
IF (PhoneN=20 and CarrierN=4) d_sst_spr=1 .
IF (PhoneN=21 and CarrierN=1) d_hi_att=1 .
IF (PhoneN=21 and CarrierN=2) d_hi_vz=1 .
IF (PhoneN=21 and CarrierN=3) d_hi_tm=1 .
IF (PhoneN=21 and CarrierN=4) d_hi_spr=1 .
IF (PhoneN=22 and CarrierN=1) d_sa_att=1 .
IF (PhoneN=22 and CarrierN=2) d_sa_vz=1 .
IF (PhoneN=22 and CarrierN=3) d_sa_tm=1 .
IF (PhoneN=22 and CarrierN=4) d_sa_spr=1 .
IF (PhoneN=23 and CarrierN=1) d_mdb_att=1 .
IF (PhoneN=23 and CarrierN=2) d_mdb_vz=1 .
IF (PhoneN=23 and CarrierN=3) d_mbd_tm=1 .
IF (PhoneN=23 and CarrierN=4) d_mbd_spr=1 .
IF (PhoneN=24 and CarrierN=1) d_lo_att=1 .
IF (PhoneN=24 and CarrierN=2) d_lo_vz=1 .
IF (PhoneN=24 and CarrierN=3) d_lo_tm=1 .
IF (PhoneN=24 and CarrierN=4) d_lo_spr=1 .
IF (PhoneN=25 and CarrierN=1) d_mx_att=1 .
IF (PhoneN=25 and CarrierN=2) d_mx_vz=1 .
IF (PhoneN=25 and CarrierN=3) d_mx_tm=1 .
IF (PhoneN=25 and CarrierN=4) d_mx_spr=1 .
IF (CarrierN=1 and CompanyN=5) d_att_ap=1 .
IF (CarrierN=1 and CompanyN=6) d_att_ss=1 .
IF (CarrierN=1 and CompanyN=7) d_att_mo=1 .
IF (CarrierN=1 and CompanyN=8) d_att_htc=1 .
IF (CarrierN=1 and CompanyN=9) d_att_lg=1 .
IF (CarrierN=2 and CompanyN=5) d_vz_ap=1 .
IF (CarrierN=2 and CompanyN=6) d_vz_ss=1 .
IF (CarrierN=2 and CompanyN=7) d_vz_mo=1 .
```

```
IF (CarrierN=2 and CompanyN=8) d_vz_htc=1 .
IF (CarrierN=2 and CompanyN=9) d_vz_lg=1 .
IF (CarrierN=3 and CompanyN=5) d_tm_ap=1 .
IF (CarrierN=3 and CompanyN=6) d_tm_ss=1 .
IF (CarrierN=3 and CompanyN=7) d_tm_mo=1 .
IF (CarrierN=3 and CompanyN=8) d_tm_htc=1 .
IF (CarrierN=3 and CompanyN=9) d_tm_lg=1 .
IF (CarrierN=4 and CompanyN=5) d_spr_ap=1 .
IF (CarrierN=4 and CompanyN=6) d_spr_ss=1 .
IF (CarrierN=4 and CompanyN=7) d_spr_mo=1 .
IF (CarrierN=4 and CompanyN=8) d_spr_htc=1 .
IF (CarrierN=4 and CompanyN=9) d_spr_lg=1 .

* Calculating Index for BLP elasticity estimates .
IF (PhoneN=1 and CarrierN=1) br=1 .
IF (PhoneN=1 and CarrierN=2) br=26 .
IF (PhoneN=1 and CarrierN=3) br=51 .
IF (PhoneN=1 and CarrierN=4) br=76 .
IF (PhoneN=2 and CarrierN=1) br=2 .
IF (PhoneN=2 and CarrierN=2) br=27 .
IF (PhoneN=2 and CarrierN=3) br=52 .
IF (PhoneN=2 and CarrierN=4) br=77 .
IF (PhoneN=3 and CarrierN=1) br=3 .
IF (PhoneN=3 and CarrierN=2) br=28 .
IF (PhoneN=3 and CarrierN=3) br=53 .
IF (PhoneN=3 and CarrierN=4) br=78 .
IF (PhoneN=4 and CarrierN=1) br=4 .
IF (PhoneN=4 and CarrierN=2) br=29 .
IF (PhoneN=4 and CarrierN=3) br=54 .
IF (PhoneN=4 and CarrierN=4) br=79 .
IF (PhoneN=5 and CarrierN=1) br=5 .
IF (PhoneN=5 and CarrierN=2) br=30 .
IF (PhoneN=5 and CarrierN=3) br=55 .
IF (PhoneN=5 and CarrierN=4) br=80 .
IF (PhoneN=6 and CarrierN=1) br=6 .
IF (PhoneN=6 and CarrierN=2) br=31 .
IF (PhoneN=6 and CarrierN=3) br=56 .
IF (PhoneN=6 and CarrierN=4) br=81 .
IF (PhoneN=7 and CarrierN=1) br=7 .
```

```
IF (PhoneN=7 and CarrierN=2) br=32 .
IF (PhoneN=7 and CarrierN=3) br=57 .
IF (PhoneN=7 and CarrierN=4) br=82 .
IF (PhoneN=8 and CarrierN=1) br=8 .
IF (PhoneN=8 and CarrierN=2) br=33 .
IF (PhoneN=8 and CarrierN=3) br=58 .
IF (PhoneN=8 and CarrierN=4) br=83 .
IF (PhoneN=9 and CarrierN=1) br=9 .
IF (PhoneN=9 and CarrierN=2) br=34 .
IF (PhoneN=9 and CarrierN=3) br=59 .
IF (PhoneN=9 and CarrierN=4) br=84 .
IF (PhoneN=10 and CarrierN=1) br=10 .
IF (PhoneN=10 and CarrierN=2) br=35 .
IF (PhoneN=10 and CarrierN=3) br=60 .
IF (PhoneN=10 and CarrierN=4) br=85 .
IF (PhoneN=11 and CarrierN=1) br=11 .
IF (PhoneN=11 and CarrierN=2) br=36 .
IF (PhoneN=11 and CarrierN=3) br=61 .
IF (PhoneN=11 and CarrierN=4) br=86 .
IF (PhoneN=12 and CarrierN=1) br=12 .
IF (PhoneN=12 and CarrierN=2) br=37 .
IF (PhoneN=12 and CarrierN=3) br=62 .
IF (PhoneN=12 and CarrierN=4) br=87 .
IF (PhoneN=13 and CarrierN=1) br=13 .
IF (PhoneN=13 and CarrierN=2) br=38 .
IF (PhoneN=13 and CarrierN=3) br=63 .
IF (PhoneN=13 and CarrierN=4) br=88 .
IF (PhoneN=14 and CarrierN=1) br=14 .
IF (PhoneN=14 and CarrierN=2) br=39 .
IF (PhoneN=14 and CarrierN=3) br=64 .
IF (PhoneN=14 and CarrierN=4) br=89 .
IF (PhoneN=15 and CarrierN=1) br=15 .
IF (PhoneN=15 and CarrierN=2) br=40 .
IF (PhoneN=15 and CarrierN=3) br=65 .
IF (PhoneN=15 and CarrierN=4) br=90 .
IF (PhoneN=16 and CarrierN=1) br=16 .
IF (PhoneN=16 and CarrierN=2) br=41 .
IF (PhoneN=16 and CarrierN=3) br=66 .
IF (PhoneN=16 and CarrierN=4) br=91 .
```

```
IF (PhoneN=17 and CarrierN=1) br=17 .
IF (PhoneN=17 and CarrierN=2) br=42 .
IF (PhoneN=17 and CarrierN=3) br=67 .
IF (PhoneN=17 and CarrierN=4) br=92 .
IF (PhoneN=18 and CarrierN=1) br=18 .
IF (PhoneN=18 and CarrierN=2) br=43 .
IF (PhoneN=18 and CarrierN=3) br=68 .
IF (PhoneN=18 and CarrierN=4) br=93 .
IF (PhoneN=19 and CarrierN=1) br=19 .
IF (PhoneN=19 and CarrierN=2) br=44 .
IF (PhoneN=19 and CarrierN=3) br=69 .
IF (PhoneN=19 and CarrierN=4) br=94 .
IF (PhoneN=20 and CarrierN=1) br=20 .
IF (PhoneN=20 and CarrierN=2) br=45 .
IF (PhoneN=20 and CarrierN=3) br=70 .
IF (PhoneN=20 and CarrierN=4) br=95 .
IF (PhoneN=21 and CarrierN=1) br=21 .
IF (PhoneN=21 and CarrierN=2) br=46 .
IF (PhoneN=21 and CarrierN=3) br=71 .
IF (PhoneN=21 and CarrierN=4) br=96 .
IF (PhoneN=22 and CarrierN=1) br=22 .
IF (PhoneN=22 and CarrierN=2) br=47 .
IF (PhoneN=22 and CarrierN=3) br=72 .
IF (PhoneN=22 and CarrierN=4) br=97 .
IF (PhoneN=23 and CarrierN=1) br=23 .
IF (PhoneN=23 and CarrierN=2) br=48 .
IF (PhoneN=23 and CarrierN=3) br=73 .
IF (PhoneN=23 and CarrierN=4) br=98 .
IF (PhoneN=24 and CarrierN=1) br=24 .
IF (PhoneN=24 and CarrierN=2) br=49 .
IF (PhoneN=24 and CarrierN=3) br=74 .
IF (PhoneN=24 and CarrierN=4) br=99 .
IF (PhoneN=25 and CarrierN=1) br=25 .
IF (PhoneN=25 and CarrierN=2) br=50 .
IF (PhoneN=25 and CarrierN=3) br=75 .
IF (PhoneN=25 and CarrierN=4) br=100 .
EXECUTE .
```

```
RECODE d_i4s_att d_i4s_vz d_i4s_tm d_i4s_spr d_i4_att d_i4_vz d_i4_tm d_i4_spr
d_i5_att d_i5_vz d_i5_tm d_i5_spr d_s3_att d_s3_vz d_s3_tm d_s3_spr d_s2_att
d_s2_vz d_s2_tm d_s2_spr d_s4_att d_s4_vz d_s4_tm d_s4_spr d_sn2_att d_sn2_vz
d_sn2_tm d_sn2_spr d_i5s_att d_i5s_vz d_i5s_tm d_i5s_spr d_mdr_att d_mdr_vz
d_mdr_tm d_mdr_spr d_he4_att d_he4_vz d_he4_tm d_he4_spr d_mdrm_att d_mdrm_vz
d_mdrm_tm d_mdrm_spr d_lm4_att d_lm4_vz d_lm4_tm d_lm4_spr d_mdrx_att
d_mdrx_vz d_mdrx_tm d_mdrx_spr d_sns_att d_sns_vz d_sns_tm d_sns_spr d_sbl_att
d_sbl_vz d_sbl_tm d_sbl_spr d_hel_att d_hel_vz d_hel_tm d_hel_spr d_ho_att d_ho_vz
d_ho_tm d_ho_spr d_ss_att d_ss_vz d_ss_tm d_ss_spr d_se_att d_se_vz d_se_tm
d_se_spr d_sst_att d_sst_vz d_sst_tm d_sst_spr d_hi_att d_hi_vz d_hi_tm d_hi_spr
d_sa_att d_sa_vz d_sa_tm d_sa_spr d_mdb_att d_mdb_vz d_mbd_tm d_mbd_spr
d_lo_att d_lo_vz d_lo_tm d_lo_spr d_mx_att d_mx_vz d_mx_tm d_mx_spr d_att_ap
d_att_ss d_att_mo d_att_htc d_att_lg d_vz_ap d_vz_ss d_vz_mo d_vz_htc d_vz_lg
d_tm_ap d_tm_ss d_tm_mo d_tm_htc d_tm_lg d_spr_ap d_spr_ss d_spr_mo d_spr_htc
d_spr_lg (1=1) (ELSE=0) .
EXECUTE .

RECODE id cdid QtrN RegionN PhoneN CarrierN CompanyN PhonePrice CarrierPrice
ScreenSize Weight TalkTime PhoneShare PhoneCost ContractLength PhoneAge AttGrp
VzGrp TmGrp SprGrp AppGrp SamGrp MotGrp HtcGrp LgGrp BbGrp NokGrp
PansGrp PantGrp SonyGrp AttNeu AttPos AttNeg VzNeu VzPos VzNeg SprNeu SprPos
SprNeg TmNeu TmPos TmNeg ForceCnt EmployCnt UnemplCnt UE_Rate
WirelessTelcom CopperWire Electrometallurgical Transportation Warehouse
Wireless372 Retail58 InorganicChem SpecialMetels Copper19011 Plastics (SYSMIS=0).
EXECUTE .

SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpDataCarReg.sav' /KEEP
id cdid QtrN RegionN PhoneN CarrierN CompanyN PhonePrice CarrierPrice ScreenSize
Weight TalkTime PhoneShare PhoneCost ContractLength PhoneAge AttGrp VzGrp
TmGrp SprGrp AppGrp SamGrp MotGrp HtcGrp LgGrp BbGrp NokGrp PansGrp
PantGrp SonyGrp AttNeu AttPos AttNeg VzNeu VzPos VzNeg SprNeu SprPos SprNeg
TmNeu TmPos TmNeg ForceCnt EmployCnt UnemplCnt UE_Rate WirelessTelcom
CopperWire Electrometallurgical Transportation Warehouse Wireless372 Retail58
InorganicChem SpecialMetels Copper19011 Plastics  d_i4s_att d_i4s_vz d_i4s_tm
d_i4s_spr d_i4_att d_i4_vz d_i4_tm d_i4_spr d_i5_att d_i5_vz d_i5_tm d_i5_spr
d_s3_att d_s3_vz d_s3_tm d_s3_spr d_s2_att d_s2_vz d_s2_tm d_s2_spr d_s4_att
d_s4_vz d_s4_tm d_s4_spr d_sn2_att d_sn2_vz d_sn2_tm d_sn2_spr d_i5s_att d_i5s_vz
d_i5s_tm d_i5s_spr d_mdr_att d_mdr_vz d_mdr_tm d_mdr_spr d_he4_att  d_he4_vz
```

```
d_he4_tm d_he4_spr d_mdrm_att d_mdrm_vz d_mdrm_tm d_mdrm_spr d_lm4_att
d_lm4_vz d_lm4_tm d_lm4_spr d_mdrx_att d_mdrx_vz d_mdrx_tm d_mdrx_spr
d_sns_att d_sns_vz d_sns_tm d_sns_spr d_sbl_att d_sbl_vz d_sbl_tm d_sbl_spr d_hel_att
d_hel_vz d_hel_tm d_hel_spr d_ho_att d_ho_vz d_ho_tm d_ho_spr  d_ss_att d_ss_vz
d_ss_tm d_ss_spr d_se_att d_se_vz d_se_tm d_se_spr d_sst_att d_sst_vz d_sst_tm
d_sst_spr d_hi_att d_hi_vz d_hi_tm d_hi_spr d_sa_att d_sa_vz d_sa_tm d_sa_spr
d_mdb_att d_mdb_vz d_mbd_tm d_mbd_spr d_lo_att d_lo_vz d_lo_tm d_lo_spr
d_mx_att d_mx_vz d_mx_tm d_mx_spr d_att_ap d_att_ss d_att_mo d_att_htc d_att_lg
d_vz_ap d_vz_ss d_vz_mo d_vz_htc d_vz_lg d_tm_ap d_tm_ss d_tm_mo d_tm_htc
d_tm_lg d_spr_ap d_spr_ss d_spr_mo d_spr_htc d_spr_lg br .

*Create excel file for MatLab read .
GET FILE
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpDataCarReg.sav' .
SAVE TRANSLATE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\MatLab\BlpCarReg\BlpData
CarReg.xlsx' /TYPE=XLS /VERSION=12 /MAP /REPLACE /FIELDNAMES
/CELLS=VALUES .
```

APPENDIX J

SPSS CODE USED TO CREATE THE COMPLEMENT BLP DEMOGRAPHIC DRAWS DATA

```
* Must run RepNelCode first .
* Population Draw .
GET FILE 'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\RepData.sav' .
RECODE MetroN (1,7,10,8,46=1) (20,25,35,41,45=2) (4,2,22,26,36,38=3)
(3,5,23,33,44,21,28=4) (6,9,24,30,31,32,42=5) INTO RegionN .
VALUE LABELS RegionN 1 'NE' 2 'SE' 3 'MW' 4 'SW' 5 'W' .
SELECT IF (NOT MISS(Income) ) .
COMPUTE RandomDraw=RV.UNIFORM(0,1).
EXECUTE.
SORT CASES BY QtrN(A) RegionN(A) RandomDraw(A) .
EXECUTE .

* Need to code the first Obs OrderN to 1 .
IF ($CASENUM=1) OrderN=1 .
IF (RegionN NE LAG(RegionN)) OrderN=1 .
EXECUTE .
IF (LAG(OrderN)=1) OrderN=2 .
IF (LAG(OrderN)=2) OrderN=3 .
IF (LAG(OrderN)=3) OrderN=4 .
IF (LAG(OrderN)=4) OrderN=5 .
IF (LAG(OrderN)=5) OrderN=6 .
IF (LAG(OrderN)=6) OrderN=7 .
IF (LAG(OrderN)=7) OrderN=8 .
IF (LAG(OrderN)=8) OrderN=9 .
IF (LAG(OrderN)=9) OrderN=10 .
IF (LAG(OrderN)=10) OrderN=11 .
IF (LAG(OrderN)=11) OrderN=12 .
IF (LAG(OrderN)=12) OrderN=13 .
IF (LAG(OrderN)=13) OrderN=14 .
IF (LAG(OrderN)=14) OrderN=15 .
IF (LAG(OrderN)=15) OrderN=16 .
IF (LAG(OrderN)=16) OrderN=17 .
IF (LAG(OrderN)=17) OrderN=18 .
IF (LAG(OrderN)=18) OrderN=19 .
```

```
IF (LAG(OrderN)=19) OrderN=20 .
EXECUTE .
FREQUENCIES VARIABLES=OrderN /ORDER=ANALYSIS .
SELECT IF (NOT MISS(OrderN)) .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpPopDrawCarReg.sav'
/KEEP=QtrN RegionN OrderN Income Age HaveKids Partner College Married Home
EthHisp EthWhite EthBlk EthAsian GenderMale Unempl Home Adults Kids HhSize
College .
GET FILE
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpPopDrawCarReg.sav' .
SORT CASES BY QtrN(A) RegionN(A) .
CASESTOVARS /ID=QtrN RegionN /INDEX=OrderN /GROUPBY=VARIABLE.
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpPopDrawsCarReg.sav' .

* Price and attribute draws .
GET FILE 'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\RepData.sav' .
RECODE MetroN (1,7,10,8,46=1) (20,25,35,41,45=2) (4,2,22,26,36,38=3)
(3,5,23,33,44,21,28=4) (6,9,24,30,31,32,42=5) INTO RegionN .
VALUE LABELS RegionN 1 'NE' 2 'SE' 3 'MW' 4 'SW' 5 'W' .
SELECT IF (NOT MISS(PhonePrice) ) .
COMPUTE RandomDraw=RV.UNIFORM(0,1).
EXECUTE.
SORT CASES BY QtrN(A) RegionN(A) RandomDraw(A) .
EXECUTE .

* Need to code the first Obs OrderN to 1 .
IF ($CASENUM=1) OrderN=1 .
IF (RegionN NE LAG(RegionN)) OrderN=1 .
EXECUTE .
IF (LAG(OrderN)=1) OrderN=2 .
IF (LAG(OrderN)=2) OrderN=3 .
IF (LAG(OrderN)=3) OrderN=4 .
IF (LAG(OrderN)=4) OrderN=5 .
IF (LAG(OrderN)=5) OrderN=6 .
IF (LAG(OrderN)=6) OrderN=7 .
IF (LAG(OrderN)=7) OrderN=8 .
IF (LAG(OrderN)=8) OrderN=9 .
```

```
IF (LAG(OrderN)=9) OrderN=10 .
IF (LAG(OrderN)=10) OrderN=11 .
IF (LAG(OrderN)=11) OrderN=12 .
IF (LAG(OrderN)=12) OrderN=13 .
IF (LAG(OrderN)=13) OrderN=14 .
IF (LAG(OrderN)=14) OrderN=15 .
IF (LAG(OrderN)=15) OrderN=16 .
IF (LAG(OrderN)=16) OrderN=17 .
IF (LAG(OrderN)=17) OrderN=18 .
IF (LAG(OrderN)=18) OrderN=19 .
IF (LAG(OrderN)=19) OrderN=20 .
EXECUTE .
FREQUENCIES VARIABLES=OrderN /ORDER=ANALYSIS .
SELECT IF (NOT MISS(OrderN)) .
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpVDrawCarReg.sav'
/KEEP=QtrN RegionN OrderN PhonePrice ScreenSize Weight TalkTime .
GET FILE
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpVDrawCarReg.sav' .
SORT CASES BY QtrN(A) RegionN(A) .
CASESTOVARS /ID=QtrN RegionN /INDEX=OrderN /GROUPBY=VARIABLE.
SAVE OUTFILE =
'C:\Users\Michael\Documents\Personal\PhD\Michael\Data\BlpVDrawsCarReg.sav' .
```

APPENDIX K

SAS CODE USED TO ESTIMATE THE MIXED LOGIT

```
libname Mix
"C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Matlab\Logit\Sas\";
data one; set Mix.Mixed;
PriceInc=PhonePrice*Income;
TtHs=TalkTime*HhSize;
run;
proc sort data=one; by rep_id PhoneN;
proc mdc data=one itprint outest=Mix.eParm; id rep_id;
model choice = PhonePrice ScreenSize Talktime Wgt PriceInc TtHs / type=mxl
choice=(PhoneN)
   mixed=(normalparm=PhonePrice ScreenSize TalkTime Wgt);
   output out=Mix.Pred p=prob xbeta=xb;
title 'random parameters logit';
ods output ParameterEstimatesResults=Mix.vardata;
run;

libname Mix
"C:\Users\Michael\Documents\Personal\PhD\Michael\Data\Matlab\Logit\Sas\";
proc sort data=Mix.Pred; by PhoneN;
proc means data=Mix.Pred; by PhoneN;
run;
```

APPENDIX L

MATLAB DATA READ CODE USED FOR THE TRADITIONAL OR SMARTPHONE ONLY BLP

```
% id.
id = xlsread('BlpDataNew.xlsx','Data','a2:a3366');

% phone index variable by qtr by metro.
cdid = xlsread('BlpDataNew.xlsx','Data','b2:b3366');

% cdindex from rc_dc.
cdindex = xlsread('BlpDataNew.xlsx','cdindex','a2:a181');

% shares .
s = xlsread('BlpDataNew.xlsx','Data','k2:k3366');

% Phone Price, Phone Dummies;
% X1 = xlsread('BlpDataNew.xlsx','Data','g2:j3366');
p = xlsread('BlpDataNew.xlsx','Data','g2:g3366');
d = xlsread('BlpDataNew.xlsx','Data','be2:cc3366');
X1 = [p./1000 d(:,1:25)];

% Need Constant, Phone Price, Screen Size, Weight, Talk Time.
X2 = xlsread('BlpDataNew.xlsx','Data','g2:j3366');

% iv variables for price.
iv = xlsread('BlpDataNew.xlsx','iv','a2:cf3366');

% phone brand index.
br = xlsread('BlpDataNew.xlsx','Data','e2:e3366');

% demographic id.
id_demo = xlsread('BlpDraw.xlsx','Demo','b2:b181');

% demographic draws (Constant,Income,Age,HaveKids).
demogr = xlsread('BlpDraw.xlsx','Demo','e2:cf181');

% random draws ordered by id_demo.
% 30 markets * 6 quarters, (Columns count of X2 matrix) * ns.
v = randn(180,100);
% v = xlsread('BlpDataNew.xlsx','v','d2:cy181');
demogr=[demogr(:,1:20)./100 demogr(:,21:40)./100
(demogr(:,21:40).*demogr(:,21:40))./100 demogr(:,41:60)./100 demogr(:,61:80)./100];
```

```
%X1=[ones(3365,1) X1(:,1:4)./1000];
X2=[ones(3365,1) X2(:,1:4)./1000];

% vcov = xlsread('vcov.xlsx','Sheet1','a1:bd56');

clear p d;
save phone.mat id id_demo cdid cdindex s X1 X2 demogr iv v br;
```

APPENDIX M

MATLAB DATA ESTIMATION CODE USED FOR THE TRADITIONAL OR SMARTPHONE ONLY BLP

```
% rcm2.m;
% X1 contains price and brand dummies
% X2 contains constant, price, Screen Size, Weight, and Talk Time

global invA ns X1 X2 s IV vfull dfull theta1 theti thetj cdid cdindex
load phone
% IV = iv(:,1:84)./1000; %Instrumental Variables
% Removes problem columns with very few non zero values
IV = [iv(:,1:16)./100 iv(:,18:20)./100 iv(:,22:41)./100 iv(:,43:45)./100 iv(:,47:66)./100
iv(:,68:70)./100 iv(:,72:84)./100];
clear iv

% Note can't recondition matrix into same name, do it in read
% Rescaling
%Demos ones, income, incomesqr, age, kids
% demogr=[demogr(:,1:20) demogr(:,21:40)./100
(demogr(:,21:40)./100).*(demogr(:,21:40)./100) demogr(:,41:60)./100
demogr(:,61:80)./100];
% demogr=[demogr(:,1:20) demogr(:,21:40) demogr(:,21:40).*demogr(:,21:40)
demogr(:,41:60) demogr(:,61:80)];
% X1=[ones(3365,1) X1(:,1:4)./100];
% X2=[ones(3365,1) X2(:,1:4)./100];
% IV(IV==0)=1; Replacing 0 with 1;

ns=20;     % number of simulated "indviduals" per market .
nmkt=30*6; % number of markets = (# of cities)*(# of quarters).

% reading cdid and cdindex from phone.mat
% When data are uniform .
% nmkt=30*6; % number of markets = (# of cities)*(# of quarters).
% nbrn=4;    % number of brands per market.
% cdid=kron([1:nmkt]',ones(nbrn,1)); % gives the market id.
% cdindex=[nbrn:nbrn:nbrn*nmkt]'; % indexes the markets.

% Random draws for the estimation.
% 30 markets * 6 quarters, (Columns count of X2 matrix) * ns.
% v = randn(nmkt,5*ns);
% v=randn(180,100);
```

```
% Each row of theta2w gives you the starting value of the parameters
% of the interaction between the variables you have in X2 and the
% unobserved and observed consumer's characteristics. In our case,
% the first row has a constant so you have
% Beta*constant*v + Beta*constant*constant + Beta*constant*Income + ...
% Beta*price*v + Beta*price*constant + Beta*price*Income + ...


%           v    Con  Income  Inc^2   Age   Kids    | Partner
theta2w=[-0.3514 -0.0456 -0.0319 -0.3668  0.9130 -0.0444;  % Constant
         0.1013 -0.0454 -0.0413 -0.0655  0.0832 -0.0128;  % Price
        -0.0335 -0.0121 -0.0123 -0.0153 -0.0417 -0.0455;  % ScreenSize
        -0.1259 -0.0458 -0.0159 -0.0989 -0.0739 -0.0452;  % Weight
        -0.0061 -0.0458 -0.0128 -0.0201 -0.0350 -0.0456]; % TalkTime

    %           v    Con  Income  Inc^2   Age   Kids    | Partner
 %theta2w=[.0000001 .000001 .000001 .000001 .000001 .000001;  % Constant
 %       0.000001 .000001 .000001 .000001 .000001 -.000001;  % Price
 %       0.000001 .000001 .000001 .000001 .000001 .000001;  % ScreenSize
 %       0.000001 .000001 .000001 .000001 .000001 -.000001;  % Weight
 %       0.000001 .000001 .000001 .000001 .000001 .000010];  % TalkTime


[theti, thetj, theta2]=find(theta2w);

horz='        mean       sigma    Cons     Income     IncomeSqr      Age     Kids';
vert=['Constant   ';
     'Price      ';
     'ScreenSize ';
     'Weight     ';
     'TalkTime   '];

  %load invA
  invA =inv(IV'*IV);
  temp=cumsum(s);
  sum1=temp(cdindex,:);
  sum1(2:size(sum1,1),:)=diff(sum1);
  outshr=1-sum1(cdid,:);
  y=log(s)-log(outshr);
  mid=X1'*IV*invA*IV';
  ttt=inv(mid*X1)*mid*y;
  mvaold=X1*ttt;
  oldt2=zeros(size(theta2));
  mvaold=exp(mvaold);
```

```
  save mvaold mvaold oldt2
  %save invA invA
  clear mid y outshr ttt oldt2 temp mvaold sum1
  vfull=v(cdid,:);
  dfull=demogr(cdid,:);
  tic
  %options=foptions;
  %options(2)=0.01;
  %options(3)=0.001;
  options=optimset('GradObj','on','TolFun',0.01,'TolX',0.01);

  [theta2,fval]=fminunc(@gmmobj, theta2, options);
  %theta2 = fmins('gmmobj',theta2)
  comp_t=toc/60;
%disp(['GMM objective:  ' num2str(options(8))])
%disp(['# of objective function evaluations:  ' num2str(options(10))])
disp(['run time (minutes):  ' num2str(comp_t)])
diary off

  vcov=var_cov(theta2);
  se=sqrt(diag(vcov));
  t = size(se,1) - size(theta2,1);
  se2w=full(sparse(theti,thetj,se(t+1:size(se,1))));
  theta=[theta1;theta2];
  tst=(theta./se);
  theta2w=full(sparse(theti,thetj,theta2));
  save results2

  % From Nevo
% the MD estimates
%omega = inv(vcov([1 2 4 5],[1 2 4 5]));
%xmd = [X2([1 2 4 5],1) X2([1 2 4 5],3:5)];
%ymd = theta1([2 3 5 6]);

omega = inv(vcov(2:26,2:26));
xmd = [X2(1:25,1) X2(1:25,2:5)];
ymd = theta1(2:26);

beta = inv(xmd'*omega*xmd)*xmd'*omega*ymd;
resmd = ymd - xmd*beta;
semd = sqrt(diag(inv(xmd'*omega*xmd)));
mcoef = [beta(1); theta1(1); beta(2:4)];
semcoef = [semd(1); se(1); semd];
```

```
Rsq = 1-((resmd-mean(resmd))'*(resmd-mean(resmd)))/((ymd-mean(ymd))'*(ymd-
mean(ymd)));
Rsq_G = 1-(resmd'*omega*resmd)/((ymd-mean(ymd))'*omega*(ymd-mean(ymd)));
Chisq = size(id,1)*resmd'*omega*resmd;

diary results
disp(horz)
disp('  ')
for i=1:size(theta2w,1)
    disp(vert(i,:))
    disp([mcoef(i) theta2w(i,:)])
    disp([semcoef(i) se2w(i,:)])
end

disp(['GMM objective:  ' num2str(options(8))])
disp(['MD R-squared:  ' num2str(Rsq)])
disp(['MD weighted R-squared:  ' num2str(Rsq_G)])
disp(['# of objective function evaluations:  ' num2str(options(10))])
disp(['run time (minutes):  ' num2str(comp_t)])
diary off

% mufunc.m;
function f = mufunc(X2,theta2w)
% This function computes the non-linear part of the utility (mu_ijt in the Guide)

% Written by Aviv Nevo, May 1998.

global ns vfull dfull
[n,k] = size(X2);
j = size(theta2w,2)-1;
mu = zeros(n,ns);
for i = 1:ns
          v_i = vfull(:,i:ns:k*ns);
       d_i = dfull(:,i:ns:j*ns);
                  mu(:,i) = (X2.*v_i*theta2w(:,1))+X2.*(d_i*theta2w(:,2:j+1)')*ones(k,1);
end
f = mu;

%mktsh.m;
function f=mktsh(mval,expmu)
```

```
global ns
f=sum((ind_sh(mval,expmu))')/ns;
f=f';

%meanval.m;
function f=meanval(theta2)

global theti thetj silent X2 s
load mvaold

if max(abs(theta2-oldt2)) < 0.01;
   tol=1e-9;
   flag=0;
else
   tol=1e-6;
   flag=1;
end

theta2w=full(sparse(theti,thetj,theta2));
expmu=exp(mufunc(X2,theta2w));

norm=1;
avgnorm=1;

i=0;

while norm > tol*10^(flag*floor(i/50))& avgnorm > 1e-3*tol*10^(flag*floor(i/50))

   mval=mvaold.*s./mktsh(mvaold,expmu);

   t=abs(mval-mvaold);
   norm=max(t);
   avgnorm=mean(t);
   mvaold=mval;
   i=i+1;
end
disp(['# of iterations for delta convergence:   ' num2str(i)])

if flag==1 & max(isnan(mval)) < 1;
```

```
   mvaold=mval;
   oldt2=theta2;
   save mvaold mvaold oldt2
end
f=log(mval);

%jacob.m;
function f=jacob(mval,theta2)

global ns theti thetj cdindex cdid
load phone

theta2w=full(sparse(theti,thetj,theta2));
expmu=exp(mufunc(X2,theta2w));
shares=ind_sh(mval,expmu);
clear expmu

[n,K]=size(X2);
J=size(theta2w,2)-1;
f1=zeros(size(cdid,1),K*(J+1));

for i=1:K
   xv=(X2(:,i)*ones(1,ns)).*v(cdid,ns*(i-1)+1:ns*i);
   temp=cumsum(xv.*shares);
   sum1=temp(cdindex,:);
   sum1(2:size(sum1,1),:)=diff(sum1);
   f1(:,i)=mean((shares.*(xv-sum1(cdid,:)))')';
   clear xv temp sum1
end

for j=1:J
   d=demogr(cdid,ns*(j-1)+1:ns*j);
   temp1=zeros(size(cdid,1),K);
   for i=1:K
      xd=(X2(:,i)*ones(1,ns)).*d;
      temp=cumsum(xd.*shares);
      sum1=temp(cdindex,:);
      sum1(2:size(sum1,1),:)=diff(sum1);
      temp1(:,i)=mean((shares.*(xd-sum1(cdid,:)))')';
```

```
      clear xd temp sum1
   end
   f1(:,K*j+1:K*(j+1))=temp1;
   clear temp1
end

rel=theti+(thetj-1)*max(theti);

f=zeros(size(cdid,1),size(rel,1));
n=1;
for i=1:size(cdindex,1)
   temp=shares(n:cdindex(i),:);
   H1=temp*temp';
   H=(diag(sum(temp'))-H1)/ns;
   f(n:cdindex(i),:)=-inv(H)*f1(n:cdindex(i),rel);
   n=cdindex(i)+1;
end
%ind_sh.m;
function f=ind_sh(expmval,expmu)
% This function gives the individual(for each consumer and brand)
% probabilities

global ns cdindex cdid
eg=expmu.*kron(ones(1,ns),expmval);
temp=cumsum(eg);
sum1=temp(cdindex,:);
sum1(2:size(sum1,1),:)=diff(sum1);
denom1=1./(1+sum1);
denom=denom1(cdid,:);
clear temp sum1
f=eg.*denom;

%gradobj.m;
function df=gradobj(theta2)

global   invA IV
%global   IV
load gmmresid
load mvaold
```

```
%load invA
temp=jacob(mvaold, theta2)';
df=2*temp*IV*invA*IV'*gmmresid;

%gmmobj.m;
function [f,g]=gmmobj(theta2)
%function f=gmmobj(theta2)

global invA theta1 theti thetj X1 IV
%global    theta1 theti thetj X1 IV

delta=meanval(theta2);
%load invA
if max(isnan(delta))==1
   f=1e+10
else
   temp1=X1'*IV;
   temp2=delta'*IV;
   theta1=inv(temp1*invA*temp1')*temp1*invA*temp2';
   clear temp1 temp2
   gmmresid=delta-X1*theta1;
   temp1=gmmresid'*IV;
   f=temp1*invA*temp1';
   clear temp1
  % invA=inv(IV'*gmmresid*gmmresid'*IV);
   save gmmresid gmmresid
   %save invA invA

   g=gradobj(theta2);
end

disp(['GMM Objective:   ' num2str(f)])

%elas.m;
%This part calculates elasticities
%Run this code after running demand side estimation
%Coded by Yan Heng, based on Knittel and Metaxoglou (2012) and Vardges
Hovhannisyan
%
```

```
%
%clear all

load results2

global invA ns X1 X2 s IV vfull dfull theta1 theta2 theti thetj cdid cdindex
muf=mufunc(X2,theta2w);
meanv=meanval(theta2);
prob=ind_sh(exp(meanv),exp(muf));
prob_1=1-prob;
% created in the read statement;
% br=data(:,1);
%Add for test. While no metro/time combinatin has 25 phones there are 25
%phone in the dataset;
nbrn=25;

vfull1=vfull(:,1:ns);
alpha_i=[];
price=X2(:,2);
   for i=1:size(vfull1,1)

alpha_i(i,:)=vfull1(i,:).*(kron(theta2(1),ones(1,ns)))+(kron(theta1(1),ones(1,ns)));
   end
   alphai=alpha_i;
   deriv_all=zeros(max(nbrn),max(nbrn),nmkt);
   elast_all=zeros(max(nbrn),max(nbrn),nmkt);

   for i=1:nmkt

      ind=cdid==i;
      pjt=price(ind,:);
      sjt=s(ind,:);
      alpha_i=alphai(ind,:);

      prob_jt=prob(ind,:);
      prob_jt_1=prob_1(ind,:);

      elast=zeros(size(pjt,1),size(pjt,1));
      deriv=zeros(size(pjt,1),size(pjt,1));
```

```
      for j=1:size(pjt,1)
         for k=1:size(pjt,1)

            if k==j
             deriv(j,j)=(1/ns)*sum(alpha_i(j,:)*(prob_jt(j,:).*prob_jt_1(j,:))');
             elast(j,j)=(pjt(j)/sjt(j))*(1/ns)*sum(alpha_i(j,:)*(prob_jt(j,:).*prob_jt_1(j,:))');
          elseif k~=j
             deriv(j,k)=(1/ns)*sum(alpha_i(j,:)*(prob_jt(j,:).*prob_jt(k,:))');
             elast(j,k)=(pjt(k)/sjt(j))*(1/ns)*sum(alpha_i(j,:)*(prob_jt(j,:).*prob_jt(k,:))');
            end
         end
      end
      elast_all(1:size(elast,1),1:size(elast,2),i)=elast;
      deriv_all(1:size(deriv,1),1:size(deriv,2),i)=deriv;

   end

   %store own and cross price elasticities
   temp=[];
   temp2=[];
   for j=1:nmkt;
      temp=[temp; (elast_all(:,:,j))];
      temp2=[temp2; diag(elast_all(:,:,j))];
   end
   elast_all=temp;
   elast_own=temp2;

%own-price elas median
e2=[];
  for i=1:max(br)
     e3=median(elast_own(br==i,:));
     e2=[e2;e3];
  end
  %cross-price elas median
     e4=[];
     for i=1:max(br)
        e5=median(elast_all(br==i,:));
        e4=[e4;e5];
```

```
end
```

APPENDIX N

MATLAB DATA READ CODE USED FOR THE COMPLEMENT BLP

```
% id.
id = xlsread('BlpDataCarRegA.xlsx','Data','a2:a1207');

% phone index variable by qtr by region.
cdid = xlsread('BlpDataCarRegA.xlsx','Data','b2:b1207');

% cdindex from rc_dc.
cdindex = xlsread('BlpDataCarRegA.xlsx','cdindex','a2:a31');

% shares .
s = xlsread('BlpDataCarRegA.xlsx','Data','m2:m1207');

% Phone Price, Carrier Price, Phone Dummies;
% X1 = xlsread('BlpDataNew.xlsx','Data','g2:j3366');
pp = xlsread('BlpDataCarRegA.xlsx','Data','h2:h1207');
cp = xlsread('BlpDataCarRegA.xlsx','Data','i2:i1207');
d = xlsread('BlpDataCarRegA.xlsx','Data','bf2:db1207');
X1 = [pp./1000 cp./1000 d(:,1:11) d(:,13:21) d(:,23:29)];
%X1=[ones(3365,1) X1(:,1:4)./1000];

% Need Constant, Phone Price, Screen Size, Weight, Talk Time.
x2 = xlsread('BlpDataCarRegA.xlsx','Data','j2:l1207');
X2=[ones(1206,1) pp./1000 cp./1000 x2(:,1:3)./1000];

% iv variables for price.
%iv = xlsread('BlpDataCarRegA.xlsx','iv','a2:fd1207');

iv1 = xlsread('BlpDataCarRegA.xlsx','iv','b2:m1207');
iv2 = xlsread('BlpDataCarRegA.xlsx','iv','fe2:gt1207');
iv=[iv1 iv2];

% phone / carrier brand index.
br = xlsread('BlpDataCarRegA.xlsx','Data','dq2:dq3366');

% demographic id.
```

```
id_demo = xlsread('BlpPopDrawsCarReg.xlsx','Demo','b2:b31');

% demographic draws (Constant,Income,Age,HaveKids).
dd = xlsread('BlpPopDrawsCarReg.xlsx','Demo','e2:cf31');
% Constant, Income, Income^2, Age, Kids
demogr=[dd(:,1:20) dd(:,21:40)./100 (dd(:,21:40).*dd(:,21:40))./100 dd(:,41:60)./100
dd(:,61:80)./100];

% random draws ordered by id_demo.
% 5 regions * 6 quarters, (Columns count of X2 matrix) * ns.
v = randn(30,120);
% v = xlsread('BlpDataNew.xlsx','v','d2:cy181');

vcov = xlsread('vcov.xlsx','Sheet1','a1:bh60');

clear pp cp d x2 dd iv1 iv2;
save phone.mat id id_demo cdid cdindex s X1 X2 demogr iv v vcov br;
```

APPENDIX O

MATLAB DATA ESTIMATION CODE USED FOR THE COMPLEMENT BLP

```
% rcm2.m;
% X1 contains price and brand dummies
% X2 contains constant, price, Screen Size, Weight, and Talk Time

global invA ns X1 X2 s IV vfull dfull theta1 theti thetj cdid cdindex
load phone

% Rescales
%     Neilsen, MEC/GRPs, Ret_58PPI, TransPPI, UE (Removing var no. 33
IV = [iv(:,1:3)./1000 iv(:,4:12)./100000 iv(:,13:26)./1000 iv(:,27:32)./1000
iv(:,34:40)./1000 iv(:,41:54)./1000];
clear iv

% Note can't recondition matrix into same name, do it in read
% Rescaling done in read statement

ns=20;     % number of simulated "indviduals" per market .
nmkt=5*6; % number of markets = (# of regions)*(# of quarters).

% reading cdid and cdindex from phone.mat
% When data are uniform .
% nmkt=5*6; % number of markets = (# of cities)*(# of quarters).
% nbrn=4;    % number of brands per market.
% cdid=kron([1:nmkt]',ones(nbrn,1)); % gives the market id.
% cdindex=[nbrn:nbrn:nbrn*nmkt]'; % indexes the markets.

% Random draws for the estimation Created in the read statement
% 5 Regions * 6 quarters, (Columns count of X2 matrix) * ns.
% v = randn(nmkt,5*ns);
% v=randn(30,120);

% Each row of theta2w gives you the starting value of the parameters
% of the interaction between the variables you have in X2 and the
% unobserved and observed consumer's characteristics. In our case,
% the first row has a constant so you have
% Beta*constant*v + Beta*constant*constant + Beta*constant*Income + ...
% Beta*price*v + Beta*price*constant + Beta*price*Income + ...

theta2w=[0.27273 -1.48383 -0.03852  0        -0.75869  -0.08010;
          -0.39543   1.85864   0.18351  0.71654   0.96308  -0.07224;
```

```
          -0.08558   0.48742   0.10868  0.24221   0.32196  -0.07792;
           0.08514   0.08843   0.08144  0         0.08398  -0.08111;
          -0.14829  -0.88041   0.02299  0        -0.38642   0.07837;
          -0.06095  -0.02521  -0.07859  0        -0.05864   0      ];

%          v       Con      Inc      Inc^2       Age      Kids
%theta2w=[.000001  .000001    .000001     0       .000001   .000001;  % Constant
%         .000001  .000001    .000001    .0000001 .000001   .000001;  % Phone Price
%         .000001  .000001    .000001    .0000001 .000001   .000001;  % Carrier Price
%         .000001  .000001    .000001     0       .000001   .000001;  % ScreenSize
%         .000001  .000001    .000001     0       .000001   .000001;  % Weight
%         .000001  .000001    .000001     0       .000001         0]; % TalkTime
[theti, thetj, theta2]=find(theta2w);

horz='                mean       sigma    Cons     Income     IncomeSqr      Age     Kids';
vert=['Constant      ';
     'Phone Price   ';
     'Carrier Price ';
     'ScreenSize    ';
     'Weight        ';
     'TalkTime      '];

  %load invA
  invA=inv(IV'*IV);
  temp=cumsum(s);
  sum1=temp(cdindex,:);
  sum1(2:size(sum1,1),:)=diff(sum1);
  outshr=1-sum1(cdid,:);
  y=log(s)-log(outshr);
  mid=X1'*IV*invA*IV';
  ttt=inv(mid*X1)*mid*y;
  mvaold=X1*ttt;
  oldt2=zeros(size(theta2));
  mvaold=exp(mvaold);
  save mvaold mvaold oldt2
  %save invA invA
  clear mid y outshr ttt oldt2 temp mvaold sum1
  vfull=v(cdid,:);
  dfull=demogr(cdid,:);
  tic
  %options=foptions;
  %options(2)=0.01;
  %options(3)=0.001;
  options=optimset('GradObj','on','TolFun',0.01,'TolX',0.01);
```

```
 [theta2,fval]=fminunc(@gmmobj, theta2, options);
 %theta2 = fmins('gmmobj',theta2)
 comp_t=toc/60;
%disp(['GMM objective:  ' num2str(options(8))])
%disp(['# of objective function evaluations:  ' num2str(options(10))])
disp(['run time (minutes):  ' num2str(comp_t)])
diary off

 % vcov=var_cov(theta2);
 se=sqrt(diag(vcov));
 t = size(se,1) - size(theta2,1);
 se2w=full(sparse(theti,thetj,se(t+1:size(se,1))));
 theta=[theta1;theta2];
 tst=(theta./se);
 theta2w=full(sparse(theti,thetj,theta2));
 save results2

% From Nevo
% the MD estimates
%omega = inv(vcov([1 2 4 5],[1 2 4 5]));
%xmd = [X2([1 2 4 5],1) X2([1 2 4 5],3:5)];
%ymd = theta1([2 3 5 6]);

omega = inv(vcov(2:26,2:26));
xmd = [X2(1:25,1) X2(1:25,2:5)];
ymd = theta1(2:26);

beta = inv(xmd'*omega*xmd)*xmd'*omega*ymd;
resmd = ymd - xmd*beta;
semd = sqrt(diag(inv(xmd'*omega*xmd)));
mcoef = [beta(1); theta1(1); beta(2:5)];
semcoef = [semd(1); se(1); semd];

Rsq = 1-((resmd-mean(resmd))'*(resmd-mean(resmd)))/((ymd-mean(ymd))'*(ymd-
mean(ymd)));
Rsq_G = 1-(resmd'*omega*resmd)/((ymd-mean(ymd))'*omega*(ymd-mean(ymd)));
Chisq = size(id,1)*resmd'*omega*resmd;

diary results
disp(horz)
disp('  ')
for i=1:size(theta2w,1)
    disp(vert(i,:))
```

```
    disp([mcoef(i) theta2w(i,:)])
    disp([semcoef(i) se2w(i,:)])
end

disp(['GMM objective:  ' num2str(options(8))])
disp(['MD R-squared:  ' num2str(Rsq)])
disp(['MD weighted R-squared:  ' num2str(Rsq_G)])
disp(['# of objective function evaluations:  ' num2str(options(10))])
disp(['run time (minutes):  ' num2str(comp_t)])
diary off

% mufunc.m;
function f = mufunc(X2,theta2w)
% This function computes the non-linear part of the utility (mu_ijt in the Guide)

% Written by Aviv Nevo, May 1998.

global ns vfull dfull
[n,k] = size(X2);
j = size(theta2w,2)-1;
mu = zeros(n,ns);
for i = 1:ns
          v_i = vfull(:,i:ns:k*ns);
       d_i = dfull(:,i:ns:j*ns);
                  mu(:,i) = (X2.*v_i*theta2w(:,1))+X2.*(d_i*theta2w(:,2:j+1)')*ones(k,1);
end
f = mu;

%mktsh.m;
function f=mktsh(mval,expmu)

global ns
f=sum((ind_sh(mval,expmu))')/ns;
f=f';

%meanval.m;
function f=meanval(theta2)

global theti thetj silent X2 s
load mvaold
```

```
if max(abs(theta2-oldt2)) < 0.01;
   tol=1e-9;
   flag=0;
else
   tol=1e-6;
   flag=1;
end

theta2w=full(sparse(theti,thetj,theta2));
expmu=exp(mufunc(X2,theta2w));

norm=1;
avgnorm=1;

i=0;

while norm > tol*10^(flag*floor(i/50))& avgnorm > 1e-3*tol*10^(flag*floor(i/50))

   mval=mvaold.*s./mktsh(mvaold,expmu);

   t=abs(mval-mvaold);
   norm=max(t);
   avgnorm=mean(t);
   mvaold=mval;
   i=i+1;
end
disp(['# of iterations for delta convergence:   ' num2str(i)])

if flag==1 & max(isnan(mval)) < 1;
   mvaold=mval;
   oldt2=theta2;
   save mvaold mvaold oldt2
end
f=log(mval);

%jacob.m;
function f=jacob(mval,theta2)
```

```
global ns theti thetj cdindex cdid
load phone

theta2w=full(sparse(theti,thetj,theta2));
expmu=exp(mufunc(X2,theta2w));
shares=ind_sh(mval,expmu);
clear expmu

[n,K]=size(X2);
J=size(theta2w,2)-1;
f1=zeros(size(cdid,1),K*(J+1));

for i=1:K
   xv=(X2(:,i)*ones(1,ns)).*v(cdid,ns*(i-1)+1:ns*i);
   temp=cumsum(xv.*shares);
   sum1=temp(cdindex,:);
   sum1(2:size(sum1,1),:)=diff(sum1);
   f1(:,i)=mean((shares.*(xv-sum1(cdid,:)))')';
   clear xv temp sum1
end

for j=1:J
   d=demogr(cdid,ns*(j-1)+1:ns*j);
   temp1=zeros(size(cdid,1),K);
   for i=1:K
      xd=(X2(:,i)*ones(1,ns)).*d;
      temp=cumsum(xd.*shares);
      sum1=temp(cdindex,:);
      sum1(2:size(sum1,1),:)=diff(sum1);
      temp1(:,i)=mean((shares.*(xd-sum1(cdid,:)))')';
      clear xd temp sum1
   end
   f1(:,K*j+1:K*(j+1))=temp1;
   clear temp1
end

rel=theti+(thetj-1)*max(theti);

f=zeros(size(cdid,1),size(rel,1));
```

```
n=1;
for i=1:size(cdindex,1)
   temp=shares(n:cdindex(i),:);
   H1=temp*temp';
   H=(diag(sum(temp'))-H1)/ns;
   f(n:cdindex(i),:)=-inv(H)*f1(n:cdindex(i),rel);
   n=cdindex(i)+1;
end
%ind_sh.m;
function f=ind_sh(expmval,expmu)
% This function gives the individual(for each consumer and brand)
% probabilities

global ns cdindex cdid
eg=expmu.*kron(ones(1,ns),expmval);
temp=cumsum(eg);
sum1=temp(cdindex,:);
sum1(2:size(sum1,1),:)=diff(sum1);
denom1=1./(1+sum1);
denom=denom1(cdid,:);
clear temp sum1
f=eg.*denom;

%gradobj.m;
function df=gradobj(theta2)

global   invA IV
%global   IV
load gmmresid
load mvaold
%load invA
temp=jacob(mvaold, theta2)';
df=2*temp*IV*invA*IV'*gmmresid;

%gmmobj.m;
function [f,g]=gmmobj(theta2)
%function f=gmmobj(theta2)

global invA theta1 theti thetj X1 IV
```

```
%global    theta1 theti thetj X1 IV

delta=meanval(theta2);
%load invA
if max(isnan(delta))==1
   f=1e+10
else
   temp1=X1'*IV;
   temp2=delta'*IV;
   theta1=inv(temp1*invA*temp1')*temp1*invA*temp2';
   clear temp1 temp2
   gmmresid=delta-X1*theta1;
   temp1=gmmresid'*IV;
   f=temp1*invA*temp1';
   clear temp1
  % invA=inv(IV'*gmmresid*gmmresid'*IV);
   save gmmresid gmmresid
   %save invA invA

   g=gradobj(theta2);
end

disp(['GMM Objective:   ' num2str(f)])

%elas.m;
%This part calculates elasticities
%Run this code after running demand side estimation
%Coded by Yan Heng, based on Knittel and Metaxoglou (2012) and Vardges
Hovhannisyan
%
%
%clear all

load results2

global invA ns X1 X2 s IV vfull dfull theta1 theta2 theti thetj cdid cdindex
muf=mufunc(X2,theta2w);
meanv=meanval(theta2);
prob=ind_sh(exp(meanv),exp(muf));
```

```
prob_1=1-prob;
% created in the read statement;
% br=data(:,1);
%Add for test. While no metro/time combinatin has 25 phones there are 25
%phone in the dataset;
nbrn=100;

vfull1=vfull(:,1:ns);
alpha_i=[];
price=X2(:,2);
   for i=1:size(vfull1,1)

alpha_i(i,:)=vfull1(i,:).*(kron(theta2(1),ones(1,ns)))+(kron(theta1(1),ones(1,ns)));
   end
   alphai=alpha_i;
   deriv_all=zeros(max(nbrn),max(nbrn),nmkt);
   elast_all=zeros(max(nbrn),max(nbrn),nmkt);

   for i=1:nmkt

      ind=cdid==i;
      pjt=price(ind,:);
      sjt=s(ind,:);
      alpha_i=alphai(ind,:);

      prob_jt=prob(ind,:);
      prob_jt_1=prob_1(ind,:);

      elast=zeros(size(pjt,1),size(pjt,1));
      deriv=zeros(size(pjt,1),size(pjt,1));

      for j=1:size(pjt,1)
         for k=1:size(pjt,1)

            if k==j
             deriv(j,j)=(1/ns)*sum(alpha_i(j,:)*(prob_jt(j,:).*prob_jt_1(j,:))');
             elast(j,j)=(pjt(j)/sjt(j))*(1/ns)*sum(alpha_i(j,:)*(prob_jt(j,:).*prob_jt_1(j,:))');
          elseif k~=j
             deriv(j,k)=(1/ns)*sum(alpha_i(j,:)*(prob_jt(j,:).*prob_jt(k,:))');
```

```
            elast(j,k)=(pjt(k)/sjt(j))*(1/ns)*sum(alpha_i(j,:)*(prob_jt(j,:).*prob_jt(k,:))');
           end
         end
       end
       elast_all(1:size(elast,1),1:size(elast,2),i)=elast;
       deriv_all(1:size(deriv,1),1:size(deriv,2),i)=deriv;

   end

   %store own and cross price elasticities
   temp=[];
   temp2=[];
   for j=1:nmkt;
      temp=[temp; (elast_all(:,:,j))];
      temp2=[temp2; diag(elast_all(:,:,j))];
   end
   elast_all=temp;
   elast_own=temp2;

%own-price elas median
e2=[];
  for i=1:max(br)
     e3=median(elast_own(br==i,:));
     e2=[e2;e3];
  end
  %cross-price elas median
     e4=[];
     for i=1:max(br)
        e5=median(elast_all(br==i,:));
        e4=[e4;e5];
     end
save results_elas
```