ESSAYS ON THE ECONOMICS OF TELEPHONES AND EVOLVING TECHNOLOGIES

by

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DISSERTATION ABSTRACT

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Telephones have changed dramatically from their introduction to their current form, and done so most significantly since the introduction of cell phones in the 1980s. This has impacted competition in the telephony market. I study this competitive impact of cell phones on the landline market through demand analysis in the first two essays; I turn my attention to the smartphone market in the final essay.

In the first essay, I examine the effect of cell phones on telephony demand using the Consumer Expenditure Survey. I develop and estimate a model of household choice using a mixed logit as a function of consumer characteristics, unobserved alternative-specific attributes, and prices. My focus is on the evolution through time. I construct market segments and track adoptions. Evidence suggests that the move to cell phones is driven by young and and large housholds. I develop and apply a decomposition of substitutability and find that substitutability differs through time.

Cell phone technologies and consumer culture have changed dramatically since 1983, affecting the level of competition in the regulated telephony market. In the second essay, I develop an empirical strategy to estimate changing demand that addresses changing technologies and preferences. I develop a flexible methodology that allows for likelihood-based estimation of a broad class of latent-dependent-variable models with time-varying

parameters. Applying my methodology with a logit model and Bayesian methods, I study the evolution of preferences. Consumers have become more price-sensitive, indicating that improvements to cell phones have provided an increasing competitive constraint on landline pricing.

In the third essay, I develop a model of the US smartphone industry; consumers demand products according to a random utility model; firms compete in a dynamic oligopoly model; I incorporate supply-side learning. Firms learn demand through time inspired by recursive least squares adaptive learning. Firms choose whether to release new devices and when to remove devices from the market according to expected future profits. I estimate fixed costs in this market, finding a competitive environment with significant fixed costs. Results show large entry costs and scrap values driven by substantial intellectual property related to technology products.

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For my wife, Laurel, who encouraged me to continue pursuing my education, and to my parents who gave me the confidence to exceed expectations.

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CHAPTER I

INTRODUCTION

The United States telecommunications industry has dramatically changed in the last four decades. Dominated by a single firm in the early 1980s, today's telephony market is dominated by multiple firms selling technology that would have been hard to recognize in the 1980s. Regulatory public policy, as well as technological advances and competitive forces, have played roles in this market's transformation that has been dramatic both in terms of the pace and the amount of change. My research focuses on the dynamic evolution of technology, competition, and demand that is essential for informing regulatory policy. Herein, I present research that implements modern demand models, develops innovative econometric tools, and incorporates theory from the industrial economics literature that builds on established models by incorporating supply-side learning.

Since the 1980s, cell phone adoption has been rapid and has reached the vast majority of consumers in the United States. Today, there are more cell phone subscriptions than there are people in the United States (cti [2013]). I begin my study of technological evolution in Chapter 2; I use a 19-year period of the Consumer Expenditure Survey to estimate household choice between telephony alternatives using discrete choice methods. The results are insensitive to different specifications I implement, and I find that the massive level of cell phone adoption is driven by both larger and younger households. Turning my attention back to the competition- and policy-relevant question of substitutability, I develop a decomposition of a substitutability measure, a measure originally formulated by Gentzkow [2007a]. Having estimated multiple logit specifications, I apply these results and my decomposition to evaluate the substitutability of cell phones for landlines. In doing so, I find that substitutability differs through time and by market segment, thereby unifying previous literature with conflicting results for different time-periods, and suggesting that in today's market, landlines do face increasing competitive effects from cell phones.

In Chapter 2, I develop and estimate a mixed logit of consumer choice, and inform the policy question of substitutability by pairing my decomposition of Gentzkow [2007a]'s substitutability measure with the results of the discrete choice model. In Chapter 3, I further study the effects of technological change on consumer demand. In particular, the change in cell phones is and has been significant over time. While observables such as price and incomes allow some changes to be directly evaluated, I develop a model in Chapter 3, motivated by Engle [2014], that allows the parameters of the utility functions to change over time. In particular, I model each parameter of the utility function as a random walk with drift. As Engle [2014] states, while there are many assumptions with which economists concern themselves, "in practice, it may be unstable regression coefficients that are most troubling. Rarely is there credible economic rationale for the assumption that the slope coefficients are time invariant." I develop a likelihood approach to estimating time-varying parameter models with latent dependent-variables for use in discrete choice. I then use this technique to estimate a discrete choice logit model using Bayesian methods in the US telephony market. This work uses Adaptive Metropolis Hastings and my adaptation of Fernández-Villaverde and Rubio-Ramírez [2004]'s sequential Monte Carlo algorithm and shows that, in addition to the insights presented in Chapter 2, consumer households are more price sensitive through time. Specifically, this work separates the improved technology of the cell phone alternative from its effect on price sensitivity by making landlines less essential for all households.

If cellular telephony developed significantly from its US debut until the mid-2000s, it is smartphones that have developed significantly since then. Characterized by the latest-and-greatest technology and inflated advertising budgets, the smartphone is the juggernaut in today's US technology market. Indeed, the highest selling individual device brand, the Apple iPhone, is a large part of Apple Inc.'s claim as one of the largest company in the world by market cap. In Chapter 4, I turn my attention to this segment of the cell phone market to understand the way in which firms compete, the costs associated with innovation and product development, and the value of different product attributes to consumers. I develop a dynamic theoretical model of competition in the spirit of Ericson and Pakes [1995a]. I follow Bajari et al. [2007]'s estimation methodology and extend it to allow for supply-side learning with an iterative version of Berry et al. [1995] with which firms learn about demand for product attributes through time. I find evidence of substantial fixed costs for firms associated with both entering the market, and releasing devices once entered and competing in the market. Additionally, my work reveals that these entry costs are similar in magnitude to scrap values reflecting the substantial role of intellectual property in this market; that is, firms have the ability to sell their intellectual property if they exit the market.

As discussed, each chapter focuses on applied research modelling a policy-relevant problem related to US telecommunications markets. Each focuses first on describing the relevant problem and what has been done to research it in the past. I then turn my attention to a conceptual model about how the market works and how this can be modelled empirically. I then present an empirical strategy to econometrically estimate the model using data. In each of the chapters, I apply different econometric tools. The second uses maximum likelihood, the third uses Bayesian econometric methods, and the fourth chapter includes generalized method of moments, instrumental variables, and a minimum distance estimator. I then present results and the value of those contributions, and conclude. Chapter 5 reiterates the contributions of, and concludes, my dissertation research.

CHAPTER II

TELEPHONY CHOICES AND THE EVOLUTION OF CELL PHONES

Introduction

Over the last three decades, telephony markets have changed dramatically due to the divestiture of the local telephone operations of AT&T, the Telecommunications Act of 1996, and the introduction of cellular telephones. The first cell phone call was made in 1973, and in 1983 cell phones were made commercially available. While growth was initially slow, cell phone usage has expanded rapidly over the last 20 years as a result of lower prices, new service offerings, and network effects. My primary objective in this paper is to examine the effects of the introduction and adoption of cell phones. I focus on household choices of telephony over time and by market segment. This allows me to identify growth segments and to examine the policy question of substitutability by market segment over time. I employ and extend a substitutability measure developed by Gentzkow [2007b]. The extension allows a decomposition of the substitutability measure by source. My research makes two primary contributions to the literature. First, my results point directly to the impact cell phones have had on the broader telephony market and what has driven this impact. Second, I develop and apply a methodology that decomposes substitutability by source and points to the evolution of the market. This methodology can be employed to investigate substitutability in a variety of evolving markets.

The landline service market has been highly regulated and the broader telephony market is one that impacts the vast majority of individuals living in the United States. In 1984, there was a divestiture of AT&T's local landline operations after a landmark antitrust case.[1] This, along with the Telecommunications Act of 1996, brought significant regulatory effects on the landline market. The simultaneous appearance and evolution of cell phones only propagated further competitive effects on the previously uncompetitive market. One of the primary questions is to what degree the availability of cell phones limits landline pricing. As recently as 2008, the Department of Justice [2008] reported that "The size of [the] wireless substitution effect is not known..." and "the available evidence does not establish that mobile services currently represent an effective competitive constraint on landline access pricing." Others disagree, including Taylor and Ware [2008] who responded that "data on price trends and substitution of cell for landline services show that mobile services currently represent an effective competitive constraint on landline access pricing." The question needs further investigation and more definitive, quantifiable answers, which I provide. In particular, this issue comes down to the extent to which cell phone services have become effective substitutes for landline services. I estimate demand and substitutability through time and find that developments in cell phone service since the implementation of the Telecommunications Act of 1996 have changed the competitive environment for landline telephony providers. This has happened in ways similar to those discussed by Gentzoglanis and Henten [2010] when discussing intermodal competition; telecommunications networks have converged so that networks originally designed to carry one type of traffic can now carry a variety of traffic types. Indeed, these changes "have made retail markets for telecommunications services effectively competitive" (Gentzoglanis and Henten [2010]). All of this points to diminished need for regulation in the landline market.

There are a number of studies that examine the demand for telephony services. These studies, e.g. Train et al. [1987], examine the choice between different pricing mechanisms, i.e. measured service versus flat fee service. Rodini et al. [2003a] examine

[1] Further discussion of this regulatory change through the 1980s can be found in Crandall [1988].

the substitution of landline and cell phone service access. Macher et al. [2013a] examine household choices among landline and cell phone services using a portfolio approach and data from 2003 to 2010. In this study, I observe data over a more extended period of time (1994-2012) during which cell phone use increased from less than 4% of U.S. households to nearly 80%. Observing these data from the Consumer Expenditure Survey (CES), I directly examine the choices made between four options of telephony service. These options are: landline, cell phone, both landline and cell, and no service. I first frame these choices in terms of socio-economic factors. I then develop a procedure to uncover prices from the CES and estimate a fixed coefficient choice model with prices and household attributes. The price proxies from the CES are consistent with the Consumer Price Index categories for the overlapping time-periods.[2] I then extend the model to allow households to place different levels of importance on prices by estimating a mixed logit. All of my specifications also include alternative-specific dummy variables, which capture effects of unobserved product attributes. I include these multiple specifications to demonstrate the robustness of my results and provide further credibility to my price proxy.[3]

In an industry that has seen so much change, it is important to understand what has driven the evolution of market demand. The usable data run from 1994 to 2012, which is substantially longer than prior studies and allow estimation that considers evolution. Using the estimates, I develop consumer profiles and trace adoption rates through time. I find that there are dramatic differences across household types in their telephony choice and adoption through time. Indeed, households of young single people are far more likely

[2]I considered other options for a price measure; however, the alternatives would not allow the entirety of the 19-year sample-period to be used. I did, however, compare my measures of price with other measures during overlapping time-periods, and found that my prices trend in the same direction and are highly correlated with other measures I found.

[3]In addition to the included specifications, I estimated a binary logit for landline using cell phone price as a right-hand-side variable and found that these two services appear to be complementary. Of course, this and previous literature, e.g. Rodini et al. [2003a], further motivate specifications that consider the evolution of the industry.

to choose cell rather than landline, while those of older people or those with larger families are more likely to choose cell phones in addition to landline phones.[4]

These results also suggest that cell phones and landlines may be substitutes for some households and complements for others. Gentzkow [2007b] developed a measure to examine substitutability of hard-copy and online newspaper subscriptions, while Macher et al. [2013a] adopt it for substitutability in the telephony market. I follow Gentzkow [2007b] to examine substitutability, then develop and estimate a decomposition of this measure, which extends this literature. An important feature of my innovation is its applicability in understanding changes in the telephony market with the evolution of cell phones and in providing deeper understanding about the level of competition between technologies in the market in the past and present. I provide a framework around this decomposition and its estimation that can be adopted to study other markets in which substitutability is changing through time. As technology continues to evolve across industries, my decomposition may be conducive to understanding the changing competition between firms in related markets in a variety of evolving industries. For example, I suggest the possibility that this could be used to see how mobile technology impacts competition in the cable or broadband internet market, or how evolving infrastructure impacts competition between local transportation methods such as public transit and automobile.

Results from applying my decomposition provide strong evidence that the substitutability of cell phone and landline varies over time and by market segment. At the beginning of my sample period, most market segments view these two services as complementary. By the end of the sample period, most of these same market segments view these two services as substitutable, suggesting that the landline telephone market

[4] My results are consistent with Macher et al. [2013a] in how non-price household characteristics matter.

has experienced increasing competition from cell phones; this may guide regulatory-policy decisions based on the level of competition in the entire telephony market.

The remainder of this paper is organized as follows. Section 2.2 introduces further history and details of the telecommunications industry as well as how this paper fits in to the relevant literature. The models are detailed in Section 2.3. The data source and variables for the project are discussed in Section 2.4. Section 2.5 presents the results of the estimation followed by Section 2.6, which concludes.

Background

The adoption and evolution of cell phones has had a tremendous impact in our culture. Since the original telephone was created in 1876, telephony has grown and evolved at a rapid pace. The car phone, developed in 1946, is considered to be the first step towards modern mobile communications.[5] Despite the many inconveniences that arose with these mobile devices, a large consumer base emerged (Klemens [2010]). Interest in mobile phones spurred technological innovation leading to the first cellular device.

First generation cell phones were analog based and limited to voice communication that could be connected to wired forms (Hanson [2007]). Dr. Martin Cooper, a Motorola researcher and executive, made the very first cellular phone call in 1973 (HistoryOfCellPhones.net [2008]). After several years of testing and negotiations between the government and telecommunication companies, the Federal Communications Commission (FCC), in 1983, gave permission for commercial cellular service. That same year, the first cell phone and first cell phone service provider entered the market.[6] Around the same time, 1982, the AT&T monopolization case was resolved, and subsequently forced the divestiture of the company's local landline operations by 1984. This was a

[5]The car phone was not a cellular device; instead it was a combination of radio and telephone.

[6]The Motorola DynaTAC 8000X and Ameritech Mobile Communications (Ameritech), respectively.

major change in telephony markets, but the cell phone was not yet an affordable product, available only to those with high income or with an employer covering the expense (Klemens [2010]). In 1987, the FCC opened another frequency for cell phone providers to use, which lead to the second generation (2G) cell phone.[7] The 2G phones supported text features, camera functions, and audio and video downloading (Hanson [2007]).[8] As the cost of cell phone service plans decreased, the variety of services began to grow, and cell phone towers were modified to extend the range of making calls (Hanson [2007]). As a result, cell phone service took off as a legitimate method of communication and lead the way to development of third generation (3G) cell phones. As time progressed, cellular services improved, and the capability of 3G cell phones increased. The transition to 3G cell phones commenced in 2002, and by 2009, most of the world was using 3G networks. The biggest change in the 3G cell phone was its capability for data transmission.[9] Specifically, it allowed faster Internet access (Gruber [2005]).

One of the main factors that likely determined the success of the cell phone was its decreasing price through time. In the cell phone industry, technological progress is rapid and innovations are readily available to all operators in the market, so that innovative services can easily and quickly be copied by the competition. As a result, cell phone services soon became a relatively homogeneous good. The increased competition lead to price cuts and made mobile services affordable for the low-spending consumer segment, the mass market (Gruber [2005]).

Today, the number of cell phone subscriptions in the U.S. is greater than the U.S. population and there are nearly 6 billion cell phone subscribers worldwide (cti [2013]). Over 30% of all U.S. households today are cellular-only according to my data and Macher

[7] 2G cell phones used digital waves, and allowed for greater sharing of frequencies.

[8] The first text message was sent in 1992 (HistoryOfCellPhones.net [2008]).

[9] This included seamless global roaming with at least 40 times higher signal transmission rates than 2G systems.

et al. [2013a]. With this perspective, the history of cell phones shows how the continued improvement in technology, as well as the decreasing price of cell phones, resulted in a global phenomenon, which is still changing and improving to this day.

A number of studies have investigated the U.S. telecommunications industry, many focusing directly on the landline telephone market.[10] Garbacz and Thompson Jr [2003] find that subsidies are costly and ineffective in providing telephony to low-income households and that decreased costs have been responsible for the increasing market size. Alleman et al. [2010] examine universal service and argue that universal service should be defined more broadly as universal connectivity, pointing to the presumption of substitutability of different communication services.

A number of papers also estimate choice models of demand in the telephony market. Train et al. [1987] estimate a choice model and conclude that increased rates for measured service will lead to substitution of consumers to the flat-rate service. Rodini et al. [2003a] estimate the substitutability of landline and cell phone service in the U.S. using data from 2000 and 2001. They find that a second landline and a cell phone are substitutes for consumers with a single landline. They also note that this may change over time as the services become more comparable. Macher et al. [2013a] estimate a bivariate probit of household choices using data from 2003 to 2010. The authors also estimate a conditional logit model and build a framework for a portfolio consumption choice and find that household characteristics can impact the choice made and that landline and cell phone services are likely substitutes.

[10] Miravete [2002] shows that welfare effects are unchanged under different rate implementations in the demand for local telephone service in the presence of asymmetric information. Economides et al. [2008] find that firms entering the landline market have positive welfare effects through differentiation rather than through price. In Bajari et al. [2008], the authors find that "coverage is strongly valued by consumers, providing an efficiency justication for across-market mergers" in the cell phone service industry.

This paper adds to the existing literature on a number of points. I develop a choice model of households choosing between alternatives and allowing the possibility that cell and landline phones are substitutes or complements. A key element of the investigation on the research question is that the data span a much longer period than has been used in earlier literature. This allows me to examine the evolution of choice over time offering insight into how this market has evolved and a benchmark for how it may continue to evolve in the future. Specifically, the extended time frame allows identification of characteristics that drive the adoption, e.g., prices, preferences, income, etc. In a market that has changed so rapidly, models that consider the dynamic environment are beneficial to understanding what is happening in the market. My analysis also includes a mixed logit model, which avoids the independence of irrelevant alternatives problem and allows for heterogeneous responses to price (Train [2009]). Finally, I decompose the substitutability of the two service options by consumer-types and time. The unique data and methods offer similar findings to previous work, e.g. Macher et al. [2013a], but extend the literature to examine intertemporal changes by household types.

Model

The model is based on the choices consumer households make with respect to telephony options. There are four mutually exclusive and exhaustive choices that a household can make, which are:

itemsep=-4mm No telephone;

iitemsep=-4mm Landline only;

iiitemsep=-4mm Cell phone only; and

ivtemsep=-4mm Cell phone and landline.

These choices are taken to be the result of utility maximization by households where utility (U_c) consists of a deterministic component (V_c) and a random component (ε_c) where c indexes the options. In order to maximize utility, agents choose option k if and only if $U_k > U_j \ \forall \ k \neq j$. However, utility contains a component that is random to the modeler and is thus modeled as probabilistic. From above, agents choose option k with probability given by:

$$P(U_k \geq U_j) = P(V_k + \varepsilon_k \geq V_j + \varepsilon_j) = P(\varepsilon_j - \varepsilon_k \leq V_k - V_j).$$

The deterministic component, V_c, is taken as a function of individual and household characteristics, e.g. income, age, etc., as well as price and alternative-specific dummy variables. Each of the alternatives has unobserved attributes, e.g. convenience, which are captured by the alternative-specific dummy variables.[11] Given the difference in errors is logistic, the choice probabilities for individual i choosing alternative k at time t are given by:

$$P_{kit} = \frac{e^{V_{kit}}}{\sum_{j=1}^{J} e^{V_{jit}}}.$$

I estimate three specifications of the model. It is noteworthy that, as reported in Section 2.5, the common coefficients are remarkably similar across the three specifications. My approach is to estimate a model without and with prices and compare the common coefficients. The CES does not provide direct price information, but allows construction of prices.[12] My first specification is a standard multinomial logit without prices. Given that prices are constructed, this specification is included for comparison and to assess the use of

[11]In addition to estimating the three specifications with the full dataset, I estimated them year-by-year. Most of the coefficients are quite stable through time except the alternative-specific dummy variables, which have considerable drift with time. For this reason, I include the year trend variable.

[12]Multiple price variables are constructed from the expenditure data as discussed in Appendix B. My results are robust to the price construction used; estimates presented here use the algorithmic approach discussed in the appendix.

the constructed prices empirically. I then introduce prices for each option and estimate a conditional logit. My final specification is a mixed logit with a random coefficient on price using maximum simulated likelihood consistent with Train [2009]; this coefficient is log-normally distributed. Implementing the mixed logit model ameliorates the independence of irrelevant alternatives assumption required by other logit specifications, and allows for heterogeneity in responses to price.[13] The choice probabilities for individual i choosing option k at time t are given by:

$$P_{kit} = \int L_{kit}(\beta) f(\beta) d\beta,$$

where $L_{kit}(\beta)$ is the usual logit formula and $f(\beta)$ is the continuous probability density of the parameters, β; this density will be estimated. For the deterministic component of utility denoted $V_{kit}(\beta)$, the usual logit formula is given by:

$$L_{kit}(\beta) = \frac{e^{V_{kit}(\beta)}}{\sum_{j=1}^{J} e^{V_{kjt}(\beta)}}.$$

In this specification V_{kit} is taken as a function of individual and household characteristics, prices, and alternative-specific dummy variables. The alternative-specific conditional logit specification takes the same general form as the mixed logit specification but enforces the parameter on prices to be equal across all agents.

[13] The IIA assumption imposes that, when one option is taken away, there will be proportionate substitution to the other alternatives, e.g., if the no phone option is removed, IIA holds that the proportion of those individuals who did choose no-phone but now choose both among those who initially chose no-phone is equal to the proportion of individuals choosing both among those initially not choosing no-phone. In this context, I have a classic red bus / blue bus problem (Train [2009]). Those initially choosing no-phone would be unlikely to choose both, but would instead be more likely to choose either cell phone or landline in greater proportion than those who did not originally choose no-phone.

Data and Variables

The data for this project are from the CES conducted by the Bureau of Labor Statistics on a stratified sample of the United States consumer population.[14] This is an extensive survey that reports characteristics of households and individuals, detailed expenditure information, and a variety of income measures.[15] The CES contains two elements: a quarterly interview and a diary survey. The interviews are conducted on each consumer unit (CU) each quarter for five consecutive quarters[16] and capture large or consistent purchases including telephone service. Hence, this element of the survey is initially used to obtain consumption choices. I then supplement the interview data with the diary data to uncover choices captured in one, but not the other. To my knowledge, these data have not been used previously to econometrically examine telephony choices.

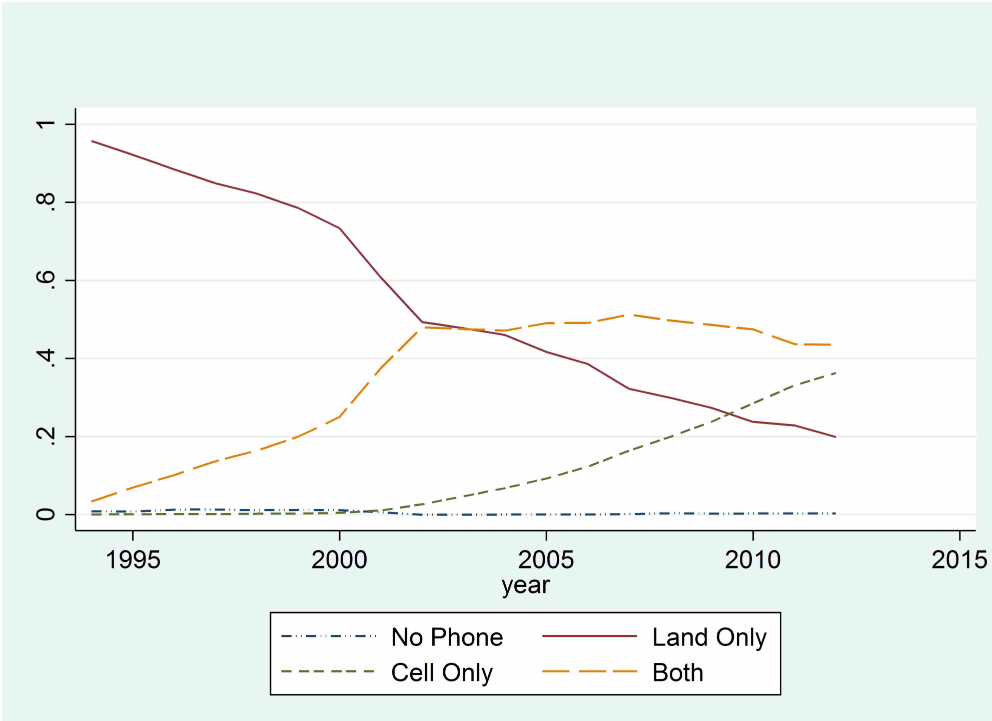
Table 1 presents the observed adoption rates by choice and year. During the earliest years of the sample, more than 90% of households chose landline while not even 4% chose a cell phone in any manner. As time continued, there was a peak in choosing both in 2007 when households selected cell phones while maintaining their landline phones. After this period in the mid-2000s, a decline begins in which the proportion of CUs choosing landline in any manner decreases. It is likely this trend will continue in future years as discussed in Section 2.5. The work of Alleman et al. [2010] points to the fact that telephony exists more broadly in a market for communications rather than for just telephone services. There are other non-telephone alternatives for communication available

[14] The stratification of the CES is intended to create representative estimates about consumer spending at the country-level. For a more detailed explanation of the stratification procedure, see BLS [2008].

[15] The expenditure information recorded is asked to households in terms of services included in the bill and is itemized, which allows for individual items on the same bill to be recorded separately. This abates problems with inappropriately recorded category expenditures that might otherwise be caused by bundled service offerings.

[16] The unit of observation is a CU-quarter, although it is possible for a CU to skip an interview quarter. In addition to estimating the models with all of the observations, I estimated each using only the first observation of each household. Doing so, I get qualitatively identical and numerically similar results.

FIGURE 1. Consumer Choice Shares



to consumers. If a CU has internet access, which may include VOIP or similar internet-based communications, that CU is still counted as no-phone if it does not subscribe to either cell phone or landline services. In whole, the early dominant choice of landline only is the only alternative to decrease over the entire sample such that it is a minority in 2012. In percentage terms, cell only has the largest gains.[17] Figure 1 contains time trends of household choices observed in the data. From these data I observe that by 2012, nearly 80% of CUs reported cell phone expenditures. These data are representative of the population of CUs and are consistent with others, e.g. Macher et al. [2013a].

Descriptive statistics of explanatory variables are provided by choice in Table 2.[18] Family Size is the number of members in a CU. Urban is a dummy variable indicating

[17]Note that for these and all estimation herein, weights are applied to observations to account for the stratification of the sample.

[18]I note that, through time, there are modest changes in the format of the questions asked in the survey. In my particular case, there were no significant changes to the definitions for the variables used.

TABLE 1. Choices Over Time

Year	No Phone	Land Only	Cell Only	Both	Total	Land or Both	Cell or Both
1994	0.83	95.72	0.05	3.40	100.00	99.12	3.45
1995	0.78	92.18	0.09	6.95	100.00	99.13	7.04
1996	1.27	88.45	0.14	10.14	100.00	98.59	10.28
1997	1.34	84.85	0.12	13.69	100.00	98.54	13.81
1998	1.13	82.23	0.22	16.42	100.00	98.65	16.64
1999	1.21	78.56	0.25	19.99	100.00	98.55	20.24
2000	1.15	73.37	0.49	24.99	100.00	98.36	25.48
2001	0.62	60.72	1.07	37.58	100.00	98.31	38.66
2002	0.00	49.31	2.69	48.00	100.00	97.31	50.69
2003	0.00	47.74	4.71	47.55	100.00	95.29	52.26
2004	0.01	46.04	6.80	47.15	100.00	93.19	53.95
2005	0.02	41.69	9.24	49.05	100.00	90.74	58.30
2006	0.02	38.61	12.28	49.09	100.00	87.70	61.37
2007	0.13	32.23	16.38	51.26	100.00	83.50	67.64
2008	0.37	29.93	19.96	49.74	100.00	79.66	69.70
2009	0.27	27.31	23.84	48.59	100.00	75.90	72.42
2010	0.28	23.76	28.51	47.45	100.00	71.21	75.97
2011	0.32	22.88	33.12	43.68	100.00	66.56	76.80
2012	0.32	19.89	36.29	43.49	100.00	63.39	79.78
Overall	0.53	54.50	10.33	34.64	100.00	89.14	44.97

whether a CU is within a metropolitan statistical area (MSA). A value of one indicates living within an MSA while a value of zero indicates living outside of all MSAs. Real income is measured in thousands of U.S. Dollars before taxes and is defined by the variable FINCBTAX in the CES deflated with a gross domestic product price deflator with base year 2005.[19]

Many of the characteristics of households are defined by the reference person and do not consider those characteristics for any other household members. For example, for a given household, race is defined only by the race of the reference person. The reference

[19]For the years 2004 and 2005, my measure of income (FINCBTAX) was not available in the CES. I used an alternative for those years (FINCBTXM) as, for years when both were available, these were highly correlated. In both cases, the nominal income variable is defined as total before-tax income over the previous 12 months for the CU including but not limited to salaries, unemployment benefits, business profits and losses, and retirement.

TABLE 2. Variable Means by Choice

	Family Size	Real Income	College	Married	Urban	Male
None	2.32	25.56	0.19	0.32	0.95	0.45
Land	2.40	35.13	0.22	0.49	0.88	0.51
Cell	2.28	36.85	0.27	0.35	0.95	0.52
Both	2.76	61.78	0.36	0.65	0.91	0.51

person is defined as the first member mentioned when asked "Start with the name of the person or one of the persons who owns or rents the home" (BLS [2008]). Race dummy variables indicate the race of the reference person: white, black, asian/pacific islander, or other, which includes native american and multi-race. Age refers to age of the reference person. Male is a dummy variable for the sex of the reference person. Married is a dummy variable indicating whether the reference person is currently married. College is a dummy variable indicating if the reference person has a bachelor's degree.

A price variable is constructed for each year using the same expenditure data used to construct the alternative choices for CUs. There are two basic processes, which suggest similar results. The simpler approach is based on the expenditures of single-person households in each category. I take the median expenditure on either service among single-person CUs who have a non-zero expenditure on the service. The other approach is based on the expenditure of households of every observed size. The basic process involves estimating the number of phones purchased by a household and then taking a median price per phone for each household size as in the previous approach. In doing so, I generate a separate price for each possible family size allowing for discounts from the purchase of multiple cell phones. For either approach, the price of the both alternative is the sum of the constructed prices for the individual options. A detailed description of each approach is presented in Appendix B.[20]

[20]For the years for which the data overlap, the correlation coefficient for my constructed price proxies and the Consumer Price Index categories of landline telephone services and wireless telephone services are 0.8681 and 0.7746, respectively. This supports the constructed prices as effective proxies for price in the

Results and Applications

The multinomial logit specification, the alternative-specific conditional logit specification, and the mixed logit specification discussed in Section 2.3 were estimated with the data described in Section 2.4. Estimates for the multinomial logit model are presented and discussed in Section 2.5. These estimates provide a base with which I compare results from the conditional and mixed logit models, which are presented and discussed in Section 2.5. These multiple specifications substantiate my price proxy since, as I discuss below, the parameter estimates for non-price variables are numerically similar and qualitatively identical across specifications.[21] Further discussion and application of the results are presented in Section 2.5.

Multinomial Logit Estimates

The coefficient estimates for the multinomial logit specification are given in Table 3. The base option is landline only, so the coefficients can generally be interpreted to imply greater utility from, although not necessarily substitution to, the alternative relative to landline for positive coefficients, and less utility from, although not necessarily substitution from, the alternative relative to landline for negative coefficients. The base category for dummy variables is a CU living in a rural location with an uneducated, single white female reference person. Real income, family size, college, married, age, and year are all

choice models. Further, I have estimated my models for the years possible using CPI rather than my price proxies and get similar results.

[21]During the time spanned by the data, cell phones and the features available have changed dramatically creating a heterogeneous product category through time. In addition to the specifications presented here, I also estimated specifications that include indicators identifying regulatory changes and cell phone features available in the marketplace. Specifically, I include indicators for the Telecommunications Act of 1996 and availability of text messaging between carriers, 3G and 4G services, Skype, the iPhone, and third-party smartphone applications. In general, these are not statistically different from zero. In fact, none are statistically different from zero at the 5% significance level. Additionally, none of these change the remaining results qualitatively or numerically.

statistically significant at the 1% significance level for each cell phone alternative. The year coefficients for all of the cell phone alternatives are positive pointing to a constant shift through time as cell phone alternatives get better relative to landline for reasons only explained by the dynamic evolution of the market. Either year fixed-effects or a trend can capture the dynamic market evolution including service changes and quality, and, having integrated year fixed-effects into one specification, these follow closely to a linear trend, so I include the linear trend here.

These results are more easily interpreted by estimating average marginal effects of explanatory variables on the probabilities. These effects are presented in Table 4. In general, a marginal effect of 0.01 implies an estimated 1% increase in probability toward that option for an associated unit-change in the relevant explanatory variable. Summing marginal effects across alternatives results in a zero value. This is to be expected since the sum total of probabilities for any given household is always 100% so that any net change must be zero. The results imply that most of the variables are significant at the 1% level. One exception is the average marginal effect of urban for the both alternative, which is only significantly different from zero for the 10% level of significance. Additionally, family size for no phone is not significant for any standard level of significance. Race dummies have varying degrees of significance.

Overall, the results in Table 4 point to the fact that demographic characteristics are important in the choice being modeled. One immediately intuitive result is that an increase in real income increases the probability of choosing both. As real income increases, consumers are more able to afford both services rather than either a single option or neither. Family size has a similar result in that an additional family member drives the probability toward the both alternative, but also toward landline and away from cell; however, the largest of these effects is towards both. This is likely driven by the increased preference for communication since consumers have more people in the family

TABLE 3. Multinomial logit

VARIABLES	None	Cell	Both
Constant	38.607**	-1049.557***	-415.080***
	(15.985)	(5.525)	(2.290)
Real Income	-0.011**	-0.003***	0.004***
	(0.004)	(0.001)	(0.001)
Family Size	-0.025	-0.217***	0.018***
	(0.025)	(0.008)	(0.004)
College	-0.864***	0.195***	0.237***
	(0.241)	(0.067)	(0.036)
Married	-0.414***	-0.325***	0.438***
	(0.079)	(0.022)	(0.012)
Urban	0.718***	0.550***	0.081***
	(0.144)	(0.043)	(0.018)
Male	-0.138**	0.372***	-0.001
	(0.064)	(0.018)	(0.010)
Black	0.173**	-0.284***	-0.133***
	(0.080)	(0.028)	(0.016)
Asian	0.312**	0.001	-0.105***
	(0.146)	(0.041)	(0.025)
Other	0.122	0.299***	0.050
	(0.257)	(0.067)	(0.043)
Age	-0.043***	-0.091***	-0.021***
	(0.003)	(0.001)	(0.000)
Year	-0.021***	0.524***	0.207***
	(0.008)	(0.003)	(0.001)
Age#Income	0.0001	0.00002***	0.00009***
	(0.000)	(0.000)	(0.000)
Age#College	0.017***	-0.006***	0.003***
	(0.006)	(0.002)	(0.001)

Note: A ***, **, or * indicates significance at the 1, 5,and 10 percent level, respectively. Standard errors are in parentheses. Landline only is the base option.

with whom they would like to communicate. I suspect this to be especially true if those additional family members are children. There are similar effects for being married, and this is likely driven by the same logic.

TABLE 4. Multinomial logit, Average Marginal Effects

VARIABLES	None	Landline	Cell	Both
Real Income	-0.00005***	-0.00117***	-0.00022***	0.00143***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Family Size	-0.00008	0.00235***	-0.01458***	0.01230***
	(0.0001)	(0.0007)	(0.0005)	(0.0007)
College	-0.00124***	-0.05499***	-0.01740***	0.07362***
	(0.0003)	(0.0020)	(0.0012)	(0.0022)
Married	-0.00244***	-0.05582***	-0.04000***	0.09825***
	(0.0004)	(0.0021)	(0.0014)	(0.0022)
Urban	0.00258***	-0.02525***	0.02901***	-0.00634*
	(0.0004)	(0.0032)	(0.0022)	(0.0033)
Male	-0.00080**	-0.00779***	0.02388***	-0.01530***
	(0.0003)	(0.0017)	(0.0011)	(0.0018)
Black	0.00119**	0.02489***	-0.01235***	-0.01373***
	(0.0005)	(0.0026)	(0.0015)	(0.0027)
Asian	0.00196**	0.01374***	0.00422	-0.01992***
	(0.0010)	(0.0041)	(0.0025)	(0.0042)
Other	0.00047	-0.01460**	0.01783***	-0.00370
	(0.0014)	(0.0070)	(0.0043)	(0.0073)
Age	-0.00014***	0.00443***	-0.00493***	0.00063***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)
Year	-0.00051***	-0.04166***	0.02490***	0.01727***
	(0.0000)	(0.0001)	(0.0001)	(0.0001)

Note: A ***, **, or * indicates significance at the 1, 5, and 10 percent level, respectively. Standard errors are in parentheses.

Non-urban CUs are more likely to experience different service quality between alternatives in addition to experiencing larger distance and costs of travel if not using telephony to communicate. As such, living in an urban environment increases the probability of having cell phone or no phone. A final point I make here is that, whether or not a CU chooses landline, they are more likely to choose not cell phone as age increases, so it is the young households who are driving the shift towards cell phones.

While the marginal effects point to average effects of the explanatory variables through the sample, another approach to analyze the data is to define consumer profiles and track their choice probabilities through time. To do so, I consider three distinct reference groups as described below and proceed to predict the probabilities of each choice-alternative for each reference group.[22] The groups are:

1. 20-year-old single urban white male living alone with 25^{th} percentile income[23] and no college degree;
2. 40-year-old married urban white male living with 4 others with 75^{th} percentile income and a college degree; and
3. 75-year-old single urban white female living alone with 50^{th} percentile income and a college degree.

There are large differences in choice-alternative probabilities between the three reference groups that are plotted in Figures 2, 3, and 4. The relatively young and poor group experiences the largest shift towards cell phone only, while the other groups are much less likely to do so. The household of the middle-aged male is most likely to choose both, a choice that overtakes landline only around 2001, a switch that happens closer to 2008 for the retirement-aged female.

[22] Again, these point to the reference person of a household where these reference groups are households.

[23] The income percentile refers to percentile in the entire sample of CUs.

FIGURE 2. Choice Evolution of Single Urban White Male

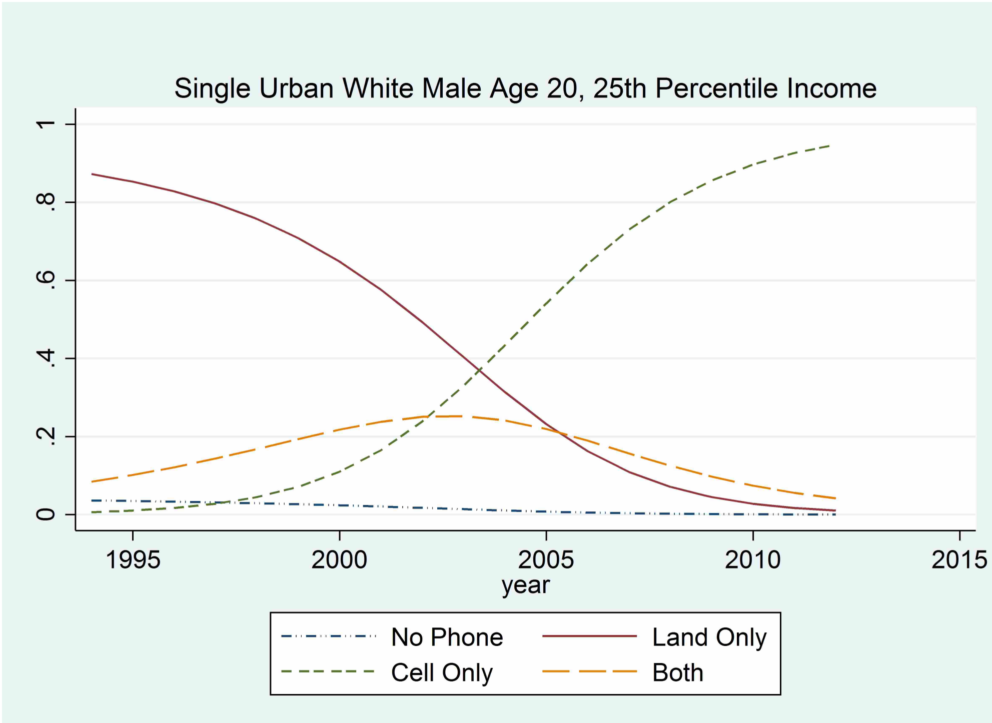


FIGURE 3. Choice Evolution of Married Urban White Male

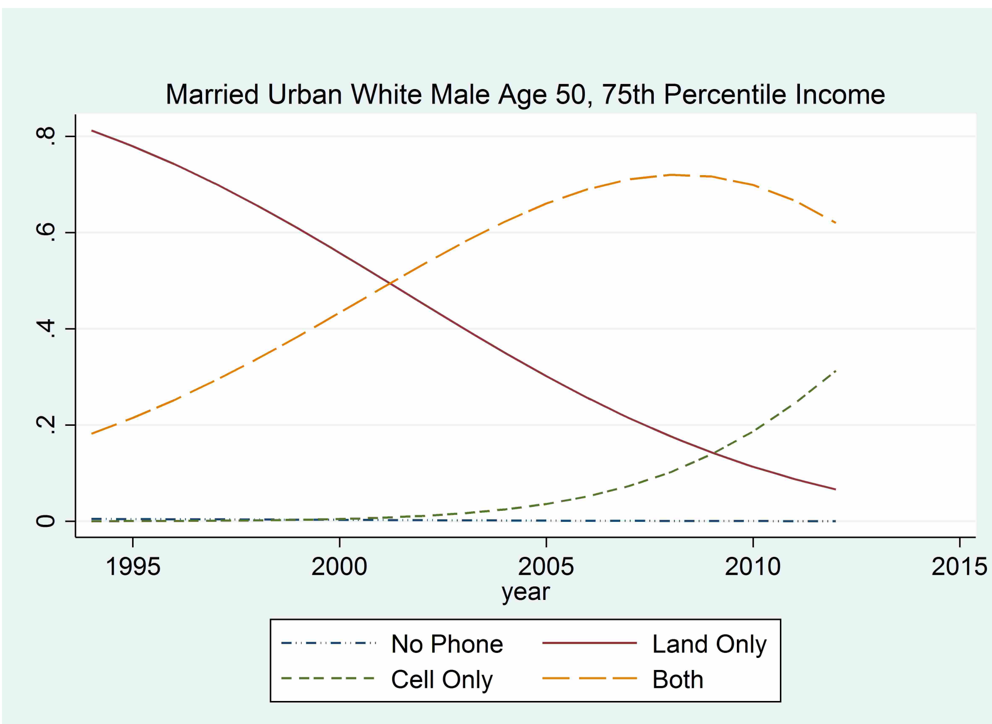
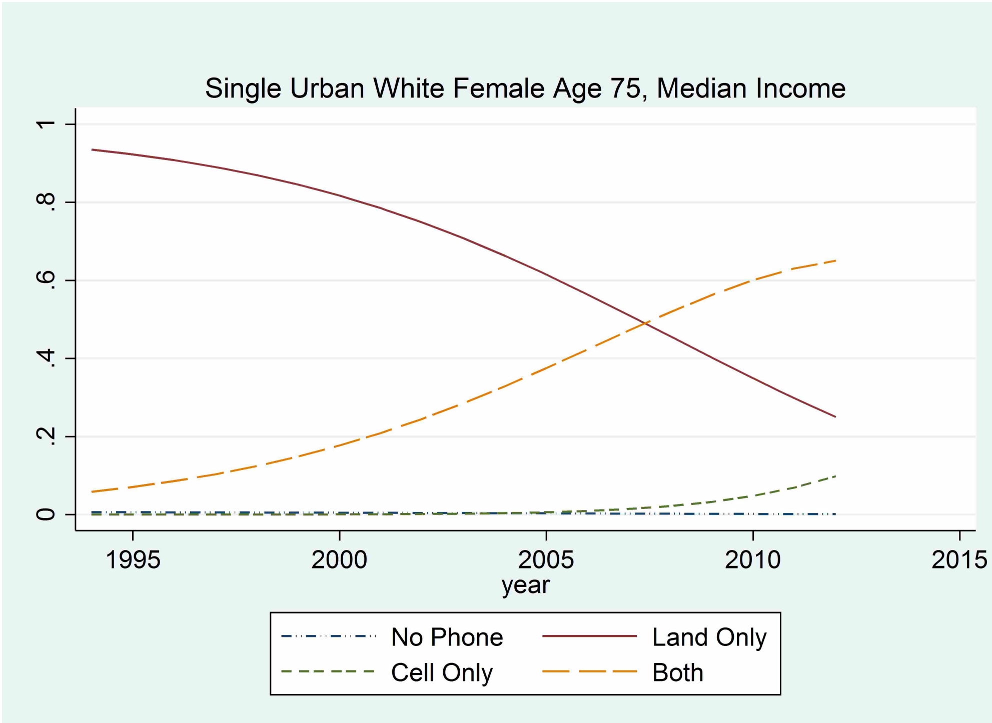


FIGURE 4. Choice Evolution of Single Urban White Female



All of the evidence thus far suggests that age of the reference person is an important factor in the choice model. I plot predicted probabilities by age every 5 years in Figures 5, 6, 7, and 8. This further illustrates the effect of age on the adoption of cell phones through time initially seen in Table 3 because this estimation procedure allows the marginal effect of age to vary over time. Younger CUs go from very high probability of landline and almost zero probability of cell phone to the extreme opposite. The CU of the middle-aged reference group has stronger adoption of both while those of the older reference group tend towards landline with very low probability of just cell phone even in 2010.

FIGURE 5. Probability by Age, 1995

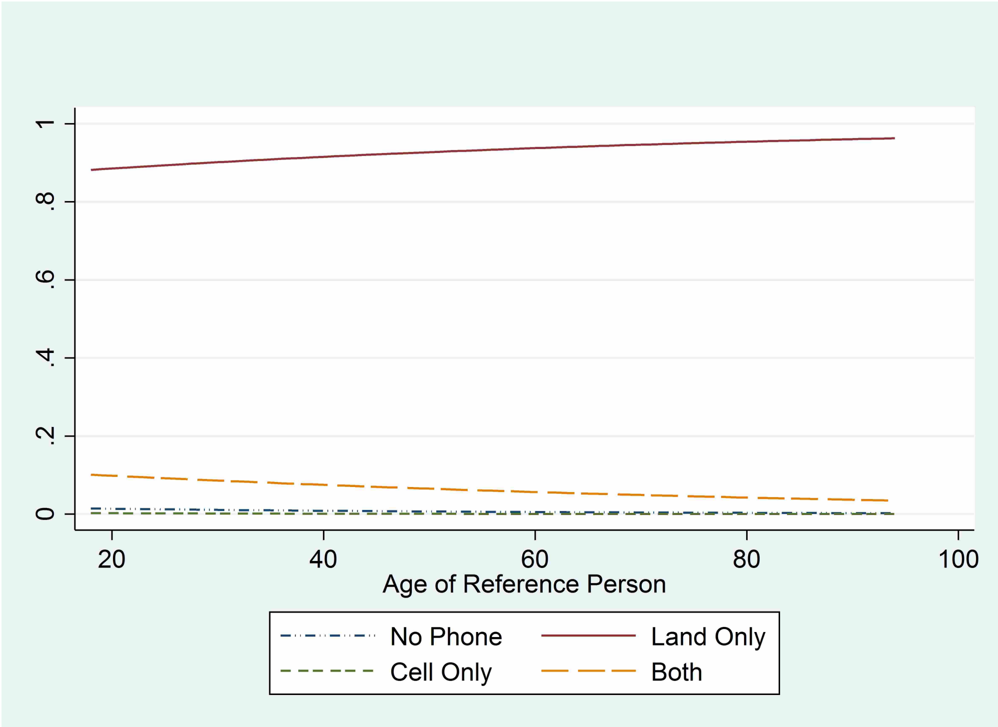


FIGURE 6. Probability by Age, 2000

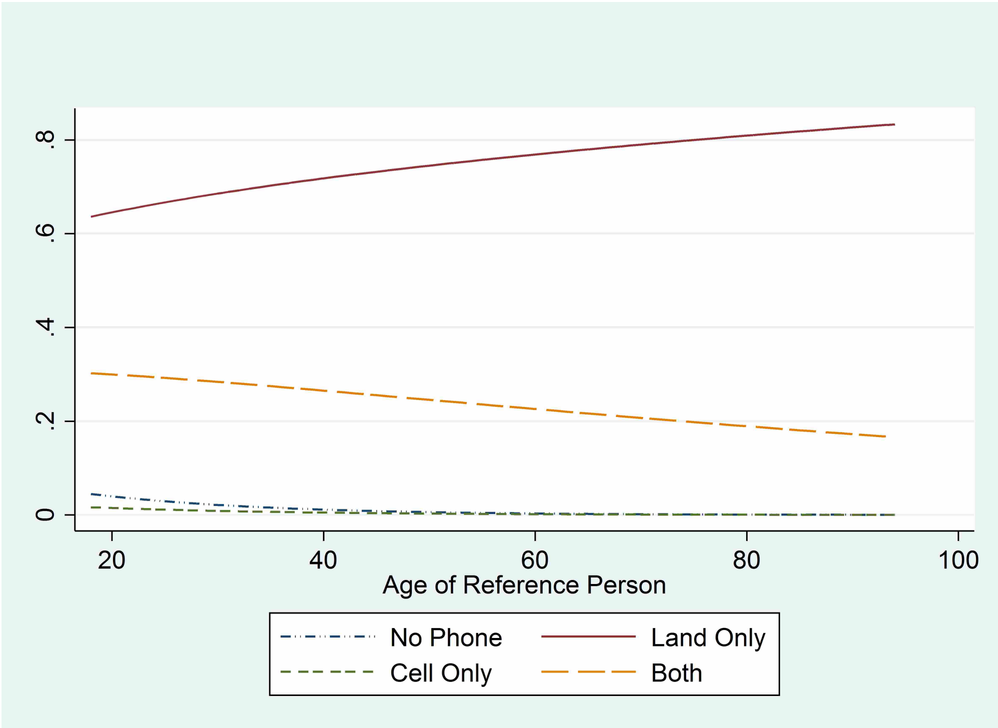


FIGURE 7. Probability by Age, 2005

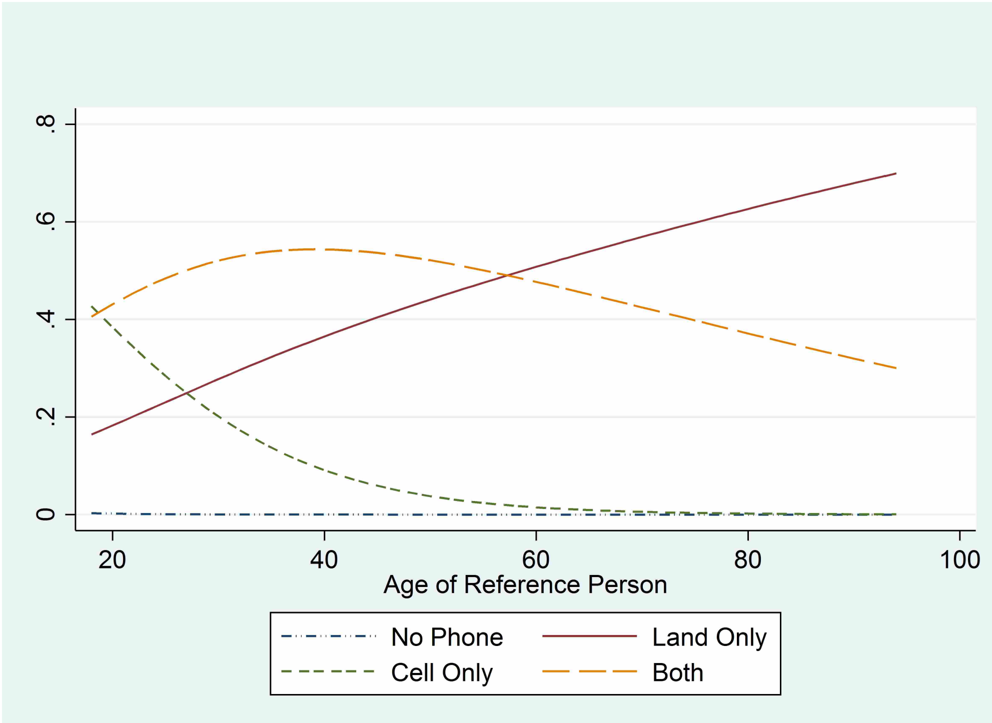
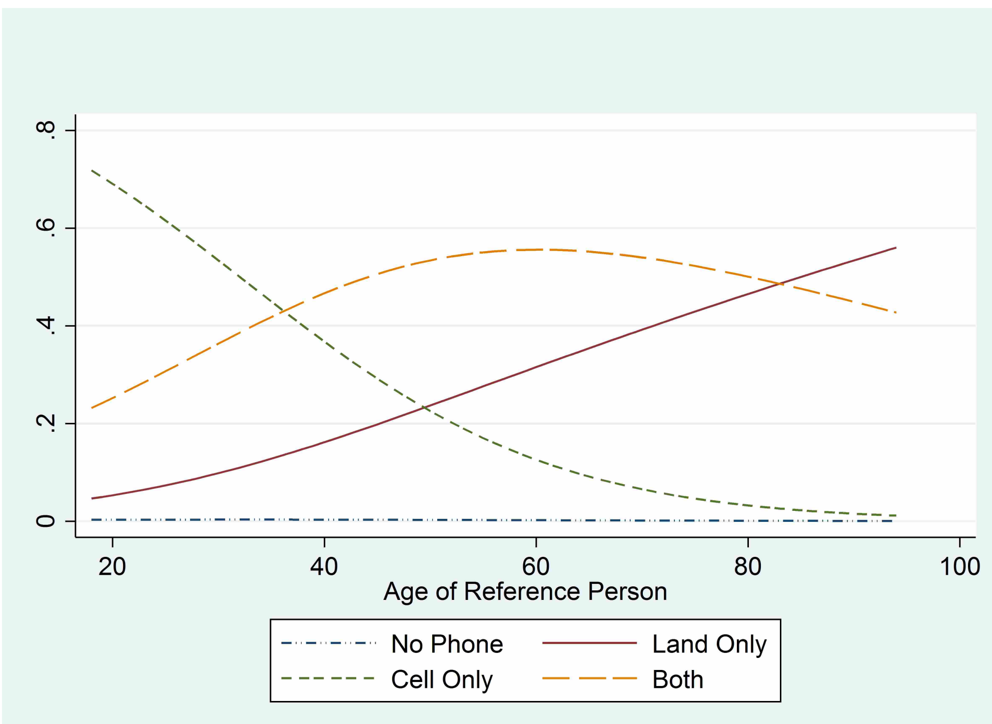


FIGURE 8. Probability by Age, 2010



Conditional and Mixed Logit Estimates

As pointed to by the significant coefficients on the trend variable in the multinomial logit results, there may be changes in the unobserved attributes of the underlying alternatives. In addition, prices have changed dramatically, and may fuel the coefficients on the trend. Unfortunately, prices are not directly available. However, using the CES data, I construct measures of alternative prices and in this section, I include these measures in the specification.[24] I estimate two models: an alternative-specific conditional logit model and a mixed logit model. The results are presented in Table 5 where, again, landline is the base option. These two specifications produce similar results which are nearly identical in the sign and significance of the shared coefficient estimates. The primary differences are the coefficient estimates on the constant, family size, and male. In each case, one model estimate provides a coefficient that is statistically significant while the other model estimate provides a coefficient that is statistically zero. Finally, the coefficient on price in the conditional logit and the mean of the distribution of price coefficients in the mixed logit are both negative and significant, but are different by two orders of magnitude. Since the results are similar, I discuss the mixed logit model in the remainder of this section.[25]

These results do suggest that increased price negatively impacts utility as expected. Since the random coefficient is assumed to have a log-normal distribution, it takes on a negative value for all households. The estimated standard deviation is statistically significant at all usual levels of significance and somewhat large relative to the mean value of the coefficient suggesting that there is wide dispersion in the coefficient value among

[24]The results here use the algorithmic approach to construct a price variable, but similar results are found using the alternative approach, which is also discussed in Appendix B.

[25]Of course the conditional logit model may suffer from independence of irrelevant alternatives assumptions. However the mixed logit does not place this a priori restriction on substitution (Train [2009]).

TABLE 5. Alternative Specific Conditional Logit and Mixed Logit Estimates

	Conditional Logit Estimates				Mixed Logit Estimates			
VARIABLES	Alt-Spec Coef	None	Cell	Both	Random Coef	None	Cell	Both
Constant		17.8560	-1060.0670***	-422.5321***		260.3457***	-1795.8070***	-1029.5320***
		(17.306)	(6.309)	(3.004)		(81.124)	(14.592)	(9.494)
Real Income		-0.0124***	-0.0033***	0.0036***		-0.0321*	-0.0012	0.0096***
		(0.005)	(0.001)	(0.001)		(0.018)	(0.001)	(0.001)
Family Size		0.0003	-0.2145***	0.0172***		0.4103**	-0.2464***	-0.0024
		(0.026)	(0.008)	(0.004)		(0.158)	(0.013)	(0.010)
College		-0.7958***	0.2062***	0.2403***		-2.0774	0.2272**	0.4209***
		(0.253)	(0.069)	(0.037)		(1.590)	(0.103)	(0.088)
Married		-0.4646***	-0.3317***	0.4313***		-1.6123***	-0.3704***	0.7777***
		(0.084)	(0.023)	(0.013)		(0.537)	(0.036)	(0.031)
Urban		0.7063***	0.5559***	0.0932***		3.1928***	0.6624***	0.0554
		(0.152)	(0.044)	(0.019)		(0.727)	(0.068)	(0.044)
Male		-0.1051*	0.3725***	0.0036		-0.3244	0.4552***	-0.0547**
		(0.069)	(0.019)	(0.011)		(0.428)	(0.030)	(0.026)
Black		0.1736**	-0.2936***	-0.1320***		0.3408	-0.4811***	-0.2532***
		(0.085)	(0.029)	(0.016)		(0.671)	(0.044)	(0.039)
Asian		0.2928**	0.0028	-0.1142***		1.5353	0.0516	-0.2752***
		(0.158)	(0.043)	(0.025)		(0.974)	(0.069)	(0.061)
Other		0.1662	0.3145***	0.0498		-1.8660***	0.5783***	0.0416
		(0.272)	(0.069)	(0.044)		(0.638)	(0.112)	(0.106)
Age		-0.0421***	-0.0912***	-0.0212***		-0.1204***	-0.1114***	-0.0272***
		(0.003)	(0.001)	(0.000)		(0.018)	(0.001)	(0.001)
Year		-0.0105	0.5297***	0.2109***		-0.1413***	0.8977***	0.5159***
		(0.009)	(0.003)	(0.002)		(0.041)	(0.007)	(0.005)
Age#Income		0.0001	0.0001***	0.0001***		0.0004	0.0001***	0.0002***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Age#College		0.0160**	-0.0063***	0.0028***		0.0540	-0.0056**	0.0084***
		(0.006)	(0.002)	(0.001)		(0.039)	(0.002)	(0.002)
Price (Mean)	-0.0025**				-0.1532***			
	(0.001)				(0.002)			
Price (Std.Dev)					0.1638***			
					(0.004)			

Note: A ***, **, or * indicates significance at the 1, 5, and 10 percent level, respectively. Standard errors are in parentheses. The second approach to computing prices is used. Landline is the base option with parameters normalized to zero.

households. This means that the response to prices is different for different households and points to the mixed logit specification. These results are also very similar to those from the multinomial logit specification. Again, in comparing the models, the few differences are entirely accounted for through one model finding a variable statistically zero while the other model does not.

Heterogeneity in Substitutability

In this section, I have presented the results from multiple specifications of discrete choice models. One central question to this paper is the substitutability of cell phone and landline phone alternatives. Gentzkow [2007b] developed a measure of substitutability that I apply and extend by developing a decomposition that allows me to examine how characteristics of market segments as well as time affect substitutability.[26] My above results provide enough information to answer this question uniquely for different groups.

Gentzkow [2007b] defines a measure, Γ, as the additional utility from consuming both options over the sum of utilities from consuming just one of those options. He does so for physical and online newspaper subscription, but the same measure can be applied to this market as in Macher et al. [2013a]. That is,

$$U_{both} = U_{cell\ only} + U_{landline\ only} + \Gamma.$$

Gentzkow [2007b] specifies that this can also be written as

$$\Gamma = (U_{both} - U_{cell}) - (U_{Landline} - U_{neither}).$$

[26] I note Macher et al. [2013a] make use of this measure as well, but do not extend or decompose it to examine heterogeneity in substitutability through time.

This is the key equation to the application as discussed below and is a useful measure that provides insight into the substitutability of two goods. For notational convenience, label the alternatives with A (cell phone), B (landline), AB (both), and N (neither). Specifically,[27]

$$\begin{aligned} \textit{Goods A and B are complements} &\iff \Gamma > 0 \\ \textit{Goods A and B are independent} &\iff \Gamma = 0 \\ \textit{Goods A and B are substitutes} &\iff \Gamma < 0 \end{aligned}$$

Using the definition above, along with the estimates from above, I compute Γ for each of the reference groups discussed in Section 2.5. Below is the extension in which I decompose Γ; this consists of a straightforward transformation and simplification of Γ defined above. Utilities for household i choosing option j are defined by:

$$U_{ij} = X_i\beta_j + Z_{ij}\alpha + \varepsilon_{ij}$$

where α and β are parameter vectors, X_i is a vector of household characteristics and alternative-specific dummy variables, Z_{ij} is a vector of characteristics that can vary over alternatives and households, and ε_{ij} is the usual error. Define deterministic utility by: $V_{ij} = X_i\beta_j + Z_{ij}\alpha$. Then for some household, i, Γ is given by:

$$\begin{aligned} \Gamma_i &= U_{i,AB} - U_{i,A} - U_{i,B} + U_{i,N} \\ &= V_{i,AB} - V_{i,A} - V_{i,B} + V_{i,N} + \tilde{\varepsilon} \end{aligned}$$

[27] For a formal proof of the following statements, see Gentzkow (2007).

where $\tilde{\varepsilon}$ is a linear combination of the random components of utilities. Taking expectations gives

$$
\begin{aligned}
E(\Gamma_i) &= X_i\beta_{AB} + Z_{ij,AB}\alpha - X_i\beta_A - Z_{ij,A}\alpha - X_i\beta_B - Z_{ij,B}\alpha + X_i\beta_N + Z_{ij,N}\alpha \\
&= X_i\left(\beta_{AB} - \beta_A - \beta_B + \beta_N\right) + \left(Z_{ij,AB} - Z_{ij,A} - Z_{ij,B} + Z_{ij,N}\right)\alpha.
\end{aligned}
$$

Note that only prices vary by alternative, i.e. $Z_i = P$, and that prices are defined by

$P_{AB} \equiv P_A + P_B$ such that the sum inside the right parentheses is definitionally zero. Further, given the base option is normalized such that $\beta_B = 0$, the expectation reduces to $E(\Gamma_i) = X_i\left(\beta_{AB} - \beta_A + \beta_N\right)$, and therefore, since $\beta_\Gamma \equiv \left(\beta_{AB} - \beta_A + \beta_N\right)$, the substitution measure of Gentzkow [2007b] can be decomposed as:

$$
\widehat{\Gamma}_i = X_i\,\widehat{\beta_\Gamma}.
$$

Noting, again, that X_i denotes a vector of household characteristics and alternative-specific dummy variables and $\widehat{\beta_\Gamma}$ is a linear combination of estimated logit parameters, an estimate can be computed directly from the existing coefficient estimates. This simple-to-compute estimator of the Γ parameter varies by individual but not by price. This is ideal for a measure of substitute goods since price changes do not play a role in their substitutability, but only drives their substitution. The true parameter illuminates whether the two goods, A and B, are complement goods or substitute goods. Specifically, when Γ_i is positive for household i, A and B are complements; when Γ_i is negative for household i, A and B are substitutes. This provides a straightforward interpretation of the estimate, defined as $\widehat{\Gamma}$, as well as the source of differences by market segments, β_Γ.

First I compute $\widehat{\Gamma}_i$ for each reference group in the beginning, middle, and end of the sample-period using the alternative-specific conditional logit specification estimates. These results are presented in Table 6. I find that, at first, two of the three reference groups view cell phone and landline phone alternatives as complements, but switch by the end of the sample period. Intuitively, this may be the result of convergence in call quality or some other explanation through time, e.g. preferences or unobserved alternative-specific attributes.

TABLE 6. Estimates of Γ_i for Reference Groups

Group	1994	2003	2012
20 year-old	-0.7420	-3.7228	-6.7035
	(0.100)	(0.086)	(0.135)
40 year-old	1.2339	-1.7468	-4.7276
	(0.120)	(0.119)	(0.164)
75 year-old	2.4445	-0.5362	-3.5170
	(0.210)	(0.200)	(0.222)

Note: Standard errors are in parentheses. $\widehat{\Gamma}_i$ constructed with conditional-logit estimates.

I also note that this substitutability measure, Γ, can be decomposed into effects from underlying sources, which, together, generate the total measure. Indeed, the measure is a linear combination of parameter estimates, $X_i\left(\beta_{AB} - \beta_A + \beta_N\right)$. By examining these parameter estimates separately from one another and without the data, I am able to decompose the substitutability by CU attributes, and I find evidence for heterogeneity in substitutability by source. These results are presented in Table 7; they suggest that for an otherwise marginal household, cell and landline phones are complements for households of older and married individuals with larger families,[28] but substitutes for those with male reference persons, higher incomes, and a college education. Maybe the most interesting estimate is that of β_Γ for the year variable, which implies that, for any given household, cell and landline phones become more likely substitutes over time based on unobserved alternative-specific attributes. For policy-makers concerned with substitutability in regard

[28]This is true for the first two specifications where the mixed logit suggests otherwise.

TABLE 7. Estimates of β_Γ

VARIABLES	Multinomial	Conditional	Mixed
Constant	673.0844***	659.1784***	1026.6210***
	(16.832)	(18.140)	(81.900)
Real Income	-0.0043	-0.0071	-0.0214
	(0.005)	(0.005)	(0.018)
Family Size	0.2106***	0.2242***	0.6542***
	(0.026)	(0.028)	(0.159)
College	-0.8214***	-0.6476**	-1.8837
	(0.249)	(0.260)	(1.594)
Married	0.3480***	0.3318***	-0.4643
	(0.082)	(0.089)	(0.538)
Urban	0.2491*	0.2496	2.5858***
	(0.150)	(0.160)	(0.730)
Male	-0.5104***	-0.5058***	-0.8343*
	(0.066)	(0.071)	(0.429)
Age	0.0268***	0.0276***	-0.0363**
	(0.003)	(0.004)	(0.018)
Year	-0.3381***	-0.3312***	-0.5231***
	(0.008)	(0.009)	(0.041)
Age#Income	0.0001	0.0001	0.0005
	(0.000)	(0.000)	(0.000)
Age#College	0.0260***	0.0222***	0.0679*
	(0.006)	(0.006)	(0.039)

Note: A ***, **, or * indicates significance at the 1, 5, and 10 percent level, respectively. Standard errors are in parentheses.

to competition in the market, this points to increasing competition in the landline market from cell phones.[29] Furthermore, my results suggest that substitutability and competition will continue to evolve in this way in the future.

[29] Another approach to calculating substitutability is to estimate elasticities. I have simulated changes in prices and predicted changes in consumption. Doing so points to elasticities, and incrementing a given variable can simulate the equivalent of β_Γ. Doing so provides results qualitatively consistent with those presented here. Simulated elasticities are available from the author upon request, but are not included here for length.

Conclusion

Cell phones have evolved dramatically over the last 20 years. While it was uncommon to see cell phones at all in the early 1990s, it is seemingly more uncommon to see someone without a cell phone today. This dramatic evolution points to serious issues with regard to investment options of service providers and to policy makers. Consumers make choices to maximize utility based on individual and household attributes, as well as characteristics of the choice alternatives. In this study, I use this framework to investigate the change in telephony choices by market segments with the evolution and dramatic adoption of cell phones.

My results provide evidence about which market segments are driving adoption and how choice probabilities have evolved. I examined choice over time and found that socio-demographic variables are important and useful to understanding household-telephony choices. Most prominently, young households are far more likely to choose cell phones as an alternative to landline phones while older households or those with larger families are more likely to choose cell phone in addition to landline phones. It is these groups, younger and larger CUs, that have driven the massive cell-phone adoption-rates observed in the data. For all consumer-types, the results display the rapid, and seemingly continued, adoption of cell phones along with, and in place of, landline phones.

I also provide quantifiable evidence on the policy question as to whether cell phone and landline services are substitutes. Cell phones can be either a substitute or a complement to landline phones and the results provide evidence that this differs by market segment and time. Further, this evidence rationalizes uncertainty from previous literature, e.g. Rodini et al. [2003a], by accounting for intertemporal changes in substitution; specifically, where studies using data from different time periods find different results, I provide evidence that this is expected as substitability has changed through time. This is among the most striking features of the results. For any given household and for all households, it is becoming more likely that these options are substitute goods through time, suggesting that the landline telephone market, as well as the broader telephony market, has seen an increase in competition from cell phones, a policy-relevant point in determining whether continued deregulation of the landline market is warranted through time.

CHAPTER III

A BAYESIAN ESTIMATOR FOR TIME-VARYING PARAMETER DISCRETE CHOICE MODELS: CHANGING DEMAND FOR CHANGING TECHNOLOGY

Introduction

Introduced to the market in 1983, cell phones have changed in form and function at a rapid pace for more than 30 years. Initially a product that only allowed calling at sky-high prices, today's smartphones are priced cheaper, yet do so much more. As such, this product has a high level of inter-temporal heterogeneity. During the same period, landline telephones have not seen much technological change. This change between competing technologies has left a trail of unanswered policy questions in the telephony market. Chief among these is the regulatory-policy question about how cell phones have impacted the broader telephony market. The Department of Justice [2008] reports that "The size of [the] wireless substitution effect is not known..." and "the available evidence does not establish that mobile services currently represent an effective competitive constraint on landline access pricing." These policy questions require timely answers, and markets with so much change require economic modeling that allows the econometrician to capture the evolution of products and the ways people use them.

In this paper, I investigate changing consumer preference parameters in evolving markets showing that changes in competing technologies can affect price sensitivity. As Engle [2014] states, "in practice, it may be unstable regression coefficients that are most troubling. Rarely is there credible economic rationale for the assumption that the slope coefficients are time invariant." In a discrete choice model, changing slope coefficients point to changes in preferences, changes in the underlying alternatives, and changes in utility. Alternatives to explicit modeling of changing preference parameters include the application of a trend variable in the specification. This is a simple approach that can capture some technological change or other dynamic features, but forces a strict form on the motion of such parameters. Similarly, dummy variables, year fixed effects, and related interaction terms also force explicit restrictions on the motion of parameters, which are frequently unmotivated and potentially arbitrary.[1] Another approach that also captures changes between time-periods is splitting the data into separate periods for estimation. This can show whether some change has occurred between these time periods, but may not offer insight into why or how the underlying data-generating process is changing.

I develop a flexible methodology that allows the estimation of a large class of models that extend existing latent dependent-variable and discrete-choice models by allowing for time-varying parameters. This is something that, to this author's knowledge, has not been done in previous literature. Specifically, I adapt the sequential Monte Carlo (SMC) filtering algorithm of Fernández-Villaverde and Rubio-Ramírez [2004] to compute the likelihood of preference parameters and parameters governing the motion of preference parameters. While this may be used for maximum likelihood estimation (MLE), I proceed using Bayesian econometric methods to estimate these parameters using Markov chain Monte Carlo (MCMC) techniques, which have a few desirable features. First, the SMC techniques applied to compute the likelihood generate draws for the preference parameters in each period of the sample as a by-product. MLE does not offer any obvious way to use these nor does MLE offer any obvious way to estimate the preference parameters for each year. Alternatively, using Bayesian methods, the yearly draws generated by the SMC filter can be used to estimate the preference parameters at each period. Bayesian methods also offer attractive features such as model selection and comparison, and the incorporation of parameter uncertainty into forecasts.

[1] That is, there is no form of motion of parameters. The "fixed-effect" for each year is independent of each other year.

Included in the newly-estimable class of models are discrete-choice logit models with time-varying parameters. I use this model to study change in the telephony market. Previous research in this market has studied the policy-relevant point of consumer choice between telephony alternatives; e.g. Train et al. [1987] consider landline access pricing and Rodini et al. [2003b] explore the substitutability of landlines and cell phones in the early 2000s. Thacker and Wilson [2015] study this issue, also using the Consumer Expenditure Survey (CES). The authors provide important answers to the policy-relevant questions posed by the Department of Justice in recent years. I extend the work of Thacker and Wilson [2015] by allowing for a more flexible model that better fits the data and captures the evolution of the products and consumers' preferences over those products. In a multinomial logit model for which the parameters are over demographic characteristics of the agents, the parameter values reflect the marginal utility of that demographic characteristic for the corresponding alternative. As I discuss in Section 3.4, these time-varying marginal utilities reflect the evolution of the choice-alternatives through time, and, specifically, relative changes in competing technologies. Maybe more compelling than the evolution of the product space is the possibility that preferences have shifted based on the way consumers use and rely on communication technologies. It is clear that technology has changed, and indeed, I find evidence that consumer demand has changed as well. Bayesian methods allow for model comparison; comparing the time-varying parameter model to its constant-parameter sibling, I find the time-varying parameter specification strongly preferred. Applying this specification, I uncover new insights into the evolution of the telephony market not detectable with existing methods.

Allowing for time-varying parameters, I find that households' preference parameters do vary through time. Specifically, the alternative-specific dummy variables, which capture the evolution of unobserved product features and technology, move dramatically from 1993 to 2012. Interestingly, consumers also become more sensitive to price. This is likely driven by the increasing cell phone service quality, and the ability of consumers to choose either service rather than needing both. Without time-varying parameters, it is impossible to capture this change in price sensitivity independent of the technological change. In addition to the variation of parameters, I explicitly model the process by which those parameters vary. For some of these parameters, there is strong evidence that a constant deterministic drift is moving the parameters rather than a simple random walk. This provides useful insight for forecasting consumer demand in the future of this still-evolving market for communication technology.

Time-varying parameters provide new insights in the telephony market, but may also inform deeper understanding of changes underlying other applied models. This framework might be implemented in foreign direct investment literature to model unobserved changes in countries' attractiveness.[2] Hazard models in health might implement this framework to capture cultural and technological changes that may better explain changes in life expectancy as it increases for all individuals in later generations.

The rest of the paper is organized as follows. Section 3.2 presents previous literature relevant to this research and discusses the telephony industry and its continued evolution through time. Section 3.3 presents the conceptual model on which Section 3.4 builds an empirical model and estimation methodology. Section 3.5 follows by presenting the data with which estimation is implemented. The empirical results are presented in Section 3.6 followed by Section 3.7, which concludes.

Background

With the many assumptions made in the empirical economics literature, rarely is it considered that the parameters may change through time. Standard alternatives include

[2] See Carlton [1983], Bartik [1985], Coughlin et al. [1991], and Head and Mayer [2004] for examples of discrete choice models of FDI.

time-period fixed effects or the inclusion of a trend variable, but this is a fundamentally different specification than truly time-varying parameters. Previous research develops methodologies for dealing with such time-varying parameters in other literatures, and in this paper, I develop a methodology that introduces time-varying parameters into the discrete-choice literature using a likelihood approach.

The use of time-varying parameters in this paper is motivated by Engle [2014], which is developed and used in the field of finance and time-series economics. While Engle [2014] includes a discussion about the assumption of time-invariant parameters, my methodology takes a different approach to estimation. Engle [2014] estimates a mean vector and covariance matrix for a time-series vector, $(y_t, x_t')'$ and generalizes the OLS formulas to include time-varying parameters, but I do not have a time-series, nor a true panel.[3] Doan et al. [1984] implement another time-series model with time-varying parameters, and like my application, they model parameters as AR(1) processes. Cogley and Sargent [2005] also implement "drifting coefficients" in the monetary policy literature noting that a "random walk specification is designed for permanent shifts" in their own application. This is fitting to the evolution of the telephony industry as well since changes in technology or culture are likely to represent permanent, rather than transitory, shifts.

This paper introduces a time-varying parameter approach for discrete choice. While this methodology can be applied to a broader class of models, I use it to extend Thacker and Wilson [2015] in which the authors investigate household choice between telephony alternatives and find strong evidence that households are heterogeneous in substitutability and that substitutability has changed through time. One important implication of changing substitutability is that other aspects of the model must also be changing. In the context of telephony, it is obvious that the products themselves have

[3]It may be possible to generalize Dynamic Conditional Beta to discrete choice with true panel data. I do not explore that possibility here.

evolved rapidly and with great consequence. To capture this in the previous work of Thacker and Wilson [2015], the authors include a trend variable that captures linear changes in the alternative-specific characteristics of the alternatives, which captures a significant amount of intertemporal product heterogeneity. A more flexible methodology can capture more variation in the evolution of alternative-specific characteristics. I use this methodology to estimate a model of the evolution of choices using revealed prefence data that span a 19-year period.

The first cell phone was invented in 1973; the first commercially-available cell phone entered the US telephony market in 1983 (Gruber [2005]). During the same time, the Department of Justice forced the divestiture of AT&T's landline operations by 1984. These changes initiated dramatic shifts in the market for telephone services. Cell phone devices have evolved tremendously since their market introduction; the original cell phone was expensive, and could make phone calls, but today, cell phones have evolved into smartphones that can access the full Internet including email, social media, geographic navigation, games, and more. Smartphones are even poised to replace cash and credit cards as a primary method of payment. Train et al. [1987] investigate substitution of consumers between different pricing schemes for landline service. Estimating a discrete choice model, the authors' results suggest that changes in rates among options will cause substitution. In a related paper, Macher et al. [2013b] develop a theoretical model that seeks to explain household choice between cell and landline phones, and then estimate choice models with data over an 8-year period of the 2000s. Results from their research suggest that landlines and cell phones are substitutes and that choices depend on household attributes. For a more complete review of the rapid and impressive evolution of the telephony market since the 1980s, and an extended review of existing literature, see Thacker and Wilson [2015].

Previous research in a variety of fields has focused on discrete choice for which agents make decisions in a dynamic environment through solving a dynamic programming problem. The seminal work of Rust [1987] develops a model of the dynamic decision process of Harold Zurcher, who decides when to replace GMC bus engines for the Madison Metropolitan Bus Company. The work of Hotz and Miller [1993] develops a method that makes estimation of the structural parameters of discrete choice dynamic programming problems less computationally burdensome and apply this method to a dynamic model of parental contraceptive choice. Additionally, Gowrisankaran and Rysman [2009] develop and estimate a dynamic model of consumer choice for new durable goods. For further review of the dynamic discrete choice literature, see Aguirregabiria and Mira [2010]. I do not observe a panel of choices being made through time by the same agents; however, the methods that I develop may be fruitful in this context as well.

Conceptual Framework

Households can choose whether to consume each alternative; specifically, an agent can choose to consume one of four mutually exclusive alternatives: (1) landline, (2) cell phone, (3) both cell phone and landline, or (4) no telephone service. They make choices to maximize their utility. Specifically, I implement the random-utility model of discrete choice such that utility contains a deterministic component and a random component. In the most general case, household i receives utility from alternative j during time-period t given by:

$$U_{ijt} = V_{ijt} + \epsilon_{ijt} = X_{it}\beta^X_{ijt} + Z_{jt}\beta^Z_{ijt} + \epsilon_{ijt}$$

where V_{ijt} is the deterministic component of utility, X_{it} are household attributes, which may change over time, Z_{jt} are alternative-specific attributes, which may also change over time, β^X_{it} and β^Z_{jt} are the effects of those on utility, respectively, and ϵ_{ijt} is the random component of utility distributed type-I extreme value. This distributional assumption is consistent with the usual class of discrete choice logit models.

The utility gained from each alternative depends on the underlying attributes of that alternative. These attributes are present in Z_{jt}, but unobserved attributes are also reflected in the parameter values over the household characteristics, β_{it}^{X}, which describe the heterogeneity in preferences by household type. As the products and their underlying attributes evolve through time, these parameters must also change. In addition, the preferences of the market participants over product attributes may evolve further suggesting that parameters vary through time. The latter point explains why β_{ijt}^{Z} varies through time, and both illustrate why β_{ijt}^{X} varies through time. To model this, the usual logit model is implemented as the measurement equation of a state-space model, and the parameter values act as the state variables, evolving according to the transition equation.

The state-space representation of this evolutionary discrete choice model takes the following form based on the specification described above:

$$Y_{it} = \underset{j \in J}{\operatorname{argmax}} \left\{ U_{ijt} = X_{it}\beta_{ijt}^{X} + Z_{jt}\beta_{it}^{Z} + \epsilon_{ijt} \right\} \tag{3.1}$$

$$\begin{bmatrix} \beta_{ijt}^{X} \\ \beta_{it}^{Z} \end{bmatrix} = \begin{bmatrix} f(\Omega_{t-1}) \\ g(\Omega_{t-1}) \end{bmatrix} + \begin{bmatrix} \omega_{ijt}^{X} \\ \omega_{it}^{Z} \end{bmatrix}. \tag{3.2}$$

Equation 3.1 is the measurement equation for a given time-period.[4] Equation 3.2 is the random state transition equation for the parameters. Y_{it} is the observed dependent variable; that is, it is the utility-maximizing alternative chosen by the household, while U_{ijt} is the latent dependent-variable representing the household's utility specific to each alternative, j. Ω_{t-1} represents data from time-period $t-1$ or earlier as well as lagged

[4]Here, I represent the discrete-choice logit model, but the method I develop is general enough to handle other discrete choice models as well.

state-variables, i.e. lagged preference parameters of the measurement equation. Here, $f(\cdot)$ and $g(\cdot)$ are the deterministic functions that, in part, determine the outcome of those parameters, and ω_{ijt}^{X} and ω_{it}^{Z} are additively separable random shocks to those parameters. At this stage, it is not necessary to make this assumption of additive-separability of the random and deterministic components in the transition equation, but I do so for expositional simplicity. More generally, this framework offers a flexible form for the transition equation; it may be linear or non-linear, and may, conditional on identification, contain a variety of random or non-random components. Note that it is possible to rewrite the measurement equation to include many non-random components that might otherwise be added to the transition equation, e.g. using interactions in the measurement equation.

Estimation Methodology

To estimate this model requires a methodology that allows for the unobserved state-variables of the transition equation, the possible non-linearity of the transition equation, the non-Gaussian error in the measurement equation, and the latent dependent-variable of the measurement equation. To accomplish this, I adapt the SMC algorithm of Fernández-Villaverde and Rubio-Ramírez [2004] to compute the value of the likelihood function. This likelihood value may then be used for Bayesian estimation via MCMC techniques or frequentist estimation via MLE. To take advantage of the relevant benefits of Bayesian estimation for the purpose of this paper, most notably the ability to estimate preference parameters for each time period, I implement the Metropolis-Hastings (MH) algorithm and proceed with estimation via MCMC.

Estimating the model requires a functional form for the measurement and transition equations. The measurement equation takes a typical logit framework where X_{it} consists of household characteristics and alternative-specific dummy variables and Z_{jt} is price.

Additionally, the parameters, i.e. β^X_{ijt} and β^Z_{it}, do not vary by individual.[5] The functional form of the transition equations for each parameter is an AR(1) process, a random walk with drift. That is, a parameter value depends only on its value in the previous period, a deterministic drift, and a random component, and these components are additively separable. Thus, for some parameter of the measurement equation, $\bar{\beta}$, the transition equation is given by:

$$\bar{\beta}_t = \bar{\beta}_{t-1} + \bar{\tau} + \omega_t, \quad \omega \sim N(0, \bar{\sigma}^2) \tag{3.3}$$

for some constant drift, $\bar{\tau}$, and some standard deviation, $\bar{\sigma}$.

MCMC Procedure

Bayesian estimation of this model involves estimating the posterior distribution of the parameter values. Specifically, I am estimating:

$$p\left(\theta \mid Y\right) = \frac{p(Y|\theta)p(\theta)}{p(Y)}$$

$$\theta = \left\{ \left\{ \left\{ \beta^k_{j0}, \tau_{jk}, \sigma_{jk} \right\}^K_{k=1} \right\}^J_{j=2}, \beta^P_0, \tau_P, \sigma_P \right\}$$

where $P\left(\theta \mid Y\right)$ is the posterior distribution to be estimated, $P(Y|\theta)$ is the likelihood function, $P(Y)$ is the prior distribution, θ is the set of estimable parameters, Y represents the data, σs are the standard deviations of the shocks to the transition equation, and βs are initial values of the preference parameters.[6]

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[5]Mixing coefficients are possible, but are currently computationally infeasible. See appendix C for further computational notes.

[6]Although I do not formally estimate preference parameters in each period as elements of θ, Bayesian econometric methods allow the draws generated by the SMC algorithm of Section 3.4 to be captured to produce estimates of these parameters in each period. Again, MLE would use the likelihood to complete estimation of θ, but would not produce these yearly estimates.

One of the standard methods for estimating the posterior distribution is to draw from it using MCMC techniques such as MH. I do so here. The basic premise of the algorithm is to draw a value for the parameters, evaluate it relative to the previous draw, and either accept or reject this value with probability α, as defined below. Doing so allows estimation of the posterior through simulation. Explicitly, the MH algorithm is given as follows.

1. Begin with a proposed value of the parameters, θ_{g-1}. For the first draw, $g = 1$, this is some initial value, θ_0.

2. Draw a new value for the parameters, θ^*, from the proposal distribution, $h(\cdot|\theta_{g-1})$.

3. Compute the MH acceptance probability of the proposal conditional on the previous draw, θ_{g-1}, by:

$$\alpha = \frac{p(Y|\theta^*)p(\theta^*)h(\theta_{g-1}|\theta^*)}{p(Y|\theta_{g-1})p(\theta_{g-1})h(\theta^*|\theta_{g-1})} \tag{3.4}$$

4. Set θ_g equal to θ^* with probability α; set θ_g equal to θ_{g-1} otherwise.

5. Return to step 2 of the algorithm for $g = g + 1$ and repeat until $g = G$ where G is the maximum number of draws.

This is the standard MH technique for drawing from the unknown posterior distribution, $p(\theta|Y)$. For further details about the process see Koop [2003]. To estimate the posterior using this technique requires computation of the distributions in the acceptance probability. Specifically, one must be able to compute the likelihood, $p(Y|\theta)$, for the proposal and the previous draw, as well as the probability density of the prior distribution at each of these values, $p(\theta)$, and the probability density of the proposal distribution for one draw conditional on another, $h(\theta|\dot{\theta})$.

Computation of the prior and proposal densities are straightforward. However, computation of the likelihood function is not straightforward due to the structure of the model; a filtering process is necessary to calculate the likelihood of a draw of θ.

Estimating the Likelihood Function

The SMC algorithm of Fernández-Villaverde and Rubio-Ramírez [2004] allows estimation of the likelihood function for nonlinear, intertemporal models, as is this model, but must be adapted to allow for the latent dependent-variable in the measurement equation of such discrete-choice models. To this author's knowledge, this has not been done by previous research. Furthermore, this approach provides a method that allows time-varying-parameters to be estimated using Bayesian methods or MLE. I proceed with the Bayesian methodology described above.

The SMC filtering algorithm estimates the value of the likelihood function as follows:

1. Set the number of particles, D, equal to a large number;

2. Take D draws of ω from the assumed distribution of equation 3.3 for each time-varying parameter;

3. Use each of these draws to calculate parameter values for the period, β_t^d, according to the transition equation and the values of the previous period;

4. Construct weights for each drawn particle based on the likelihood of the data from the period conditional on the particle's simulated parameter values:

$$\gamma_t^d = \frac{p(Y_t|\beta_t^d)}{\sum\limits_{l=1}^{D} p(Y_t|\beta_t^l)};$$

5. Redraw D draws with replacement from the original set of parameter-value draws, β_t^d, using weights given by γ_t^d. Denote these redrawn parameter values for the period by $\hat{\beta}_t^d$;

6. Return to step 2 using the redrawn parameter values, $\hat{\beta}_t^d$, as the previous period values in step 3 and repeat for the next period until reaching the end of the sample;

7. Upon reaching the end of the sample, compute the likelihood by:

$$p(Y|\theta_g) = \prod_{t=1}^{T} \frac{1}{D} \sum_{d=1}^{D} p(Y_t|\hat{\beta}_t^d). \tag{3.5}$$

Step 4 of the SMC algorithm contains the primary adaptation necessary for discrete choice. Fernández-Villaverde and Rubio-Ramírez [2004] assume measured data on the left-hand side of the measurement equation. Other latent dependent-variable models that can be estimated year-by-year can also use this procedure by computing the likelihood function for that year as the likelihood, $p(Y_t|\beta_t^d)$ in construction of the weights in step 4. For the logit model presented here, this is given by the usual logit formula. Specifically,

$$p(Y_t|\beta_t^d) = \prod_{i=1}^{N_t} \frac{exp(U_{ijt})}{\sum_{m=1}^{J} exp(U_{imt})}$$

where N_t is the number of observed choice occasions in time-period t and J is the number of available alternatives.[7] However, a variety of discrete-choice models may be estimated with time-varying parameters in this same way. Finally, note that the draws of $\hat{\beta}_t^d$ are those that I use to estimate the preference parameters at each period in time.

[7] I normalize utility constant at zero for some base alternative. This is implicit in the likelihood so that $U_{ijt} = 0 \; \forall \; i, t$ for that base alternative.

Prior Distribution

The prior distribution, $P(\theta)$, is the probability distribution over the parameters that does not include information from the data; this distribution is required for Bayesian analysis. For a variety of reasons, I implement a diffuse prior distribution that has little impact on the estimation procedure. These priors are listed for all of the estimated parameters, θ, in Table8. Specifically, I use dispersed normal distributions centered at zero for all parameters that can take on positive or negative values. For some parameter, $\widehat{\beta}$, that can take on positive or negative values, the prior distribution is given by

$$\widehat{\beta} \sim N(0, 10)$$

such that each parameter prior is independent. For all parameters that cannot take on negative values, e.g. standard deviations, I use a gamma distribution with large dispersion. For some parameter, $\widehat{\sigma}$, that cannot take on negative values, the prior distribution is given by

$$\widehat{\sigma} \sim \Gamma(1.5, 40)$$

such that each parameter prior is independent. For parameters that can only take negative values, the prior is simply the negative of this gamma distribution; specifically, my prior includes only negative values on the marginal utility of price, β_{it}^{Z}.

As stated above, there are multiple reasons for such diffuse priors. The primary reason for this is that logit models do not produce results that are easily interpreted on their own. Where some AR(1) processes might provide intuition such that the econometrician has a prior that a coefficient will be close to one and greater than zero, the parameters of the logit model do not provide straightforward intuition to guide a less diffuse prior. Further, the magnitude of logit parameters depends in part on the amount

TABLE 8. Prior Distributions for θ

ALT.	VARIABLE	PARAMETER	Distribution
	Price	β_{1993}	$N(0,10)$
		σ_ω	$\Gamma(1.5,40)$
		τ	$N(0,10)$
Cell	Constant	β_{1993}	$N(0,10)$
		σ_ω	$\Gamma(1.5,40)$
		τ	$N(0,10)$
Cell	Age	β_{1993}	$N(0,10)$
		σ_ω	$\Gamma(1.5,40)$
		τ	$N(0,10)$
Cell	Family Size	β_{1993}	$N(0,10)$
		σ_ω	$\Gamma(1.5,40)$
		τ	$N(0,10)$
Both	Constant	β_{1993}	$N(0,10)$
		σ_ω	$\Gamma(1.5,40)$
		τ	$N(0,10)$
Both	Age	β_{1993}	$N(0,10)$
		σ_ω	$\Gamma(1.5,40)$
		τ	$N(0,10)$
Both	Family Size	β_{1993}	$N(0,10)$
		σ_ω	$\Gamma(1.5,40)$
		τ	$N(0,10)$

of variation the model explains, so a prior with no information from the data cannot be excessively restrictive. Finally, a diffuse prior will let the data drive the estimation. To this point, the log-likelihoods calculated using the algorithm presented in Section 3.4 are extremely large in magnitude relative to the priors presented here. Thus, because I have a large dataset, even precise priors do not impact the estimation procedure in a meaningful way.

Proposal Distribution

The final distribution that must be addressed to carry out MH is the proposal distribution. To sample the posterior distribution in general, the ideal proposal is a random-walk proposal distribution such that

$$\theta_g \sim N(\theta_{g-1}, \kappa\Sigma_{P(\theta|Y)})$$

where θ_{g-1} is the previous draw, κ is a positive scalar, and $\Sigma_{P(\theta|Y)}$ is the true covariance matrix of the posterior distribution, $P(\theta|Y)$. For this estimation routine, I use κ equal to 2.4, as is suggested in Haario et al. [2005] for their application; this provides a satisfactory acceptance rate for my application. Given that the true posterior cannot be known during estimation of the posterior, I follow Haario et al. [2005] and implement single-component adaptive Metropolis (SCAM). This is an adaptive proposal that uses the variance of each parameter in the simulated posterior up to draw g to approximate the true posterior covariance matrix. This does cause MH to not be truly Markovian, but as discussed in Haario et al. [2005], this does not impact the properties of the estimation routine.[8]

One alternative to SCAM is adaptive metropolis (AM) of Haario et al. [2001]. This is a similar proposal but estimates the full covariance matrix of the simulated posterior up to draw g. Computing the full covariance matrix each draw is computationally taxing, so SCAM is implemented as a next-best alternative. Specifically, the variance of the k^{th} individual parameter can be updated after each draw according to

$$\widehat{\Sigma^k_{g+1}} = \frac{g-1}{g}\widehat{\Sigma^k_g} + (\overline{\theta}^k_{g-1})^2 + \frac{1}{g}(\theta^k_g)^2 - \frac{g+1}{g}(\overline{\theta}^k_g)^2$$

where g is the number of the most recent draw, $\widehat{\Sigma^k_g}$ is the k^{th} diagonal element of the simulated $\Sigma_{P(\theta|Y)}$ up to draw g, and $\overline{\theta}^k_g$ is the k^{th} element of the mean vector of the simulated posterior distribution up to the g^{th} draw. This is computationally convenient and allows for more efficient sampling of the posterior.

[8]Most notably, it is still ergodic.

Finally, note that the proposal distribution is symmetric. This allows me to simplify the acceptance probability of the MH algorithm descibed in Section 3.4. I do so by cancelling out the symmetric, and therefore equal, proposal distribution from the numerator and denominator.

Data

The data for this application come from the CES conducted by the U.S. Bureau of Labor Statistics. This is an extensive survey that asks households for expenditure information. Specifically, the CES provides expenditure information for a given household from both a quarterly interview and a daily diary over a 5-quarter period. In this application, the expenditure information is used to infer consumption choices.[9] In addition to these expenditures, the households provide a wide variety of demographic information including number of household members, age, sex, a variety of income measures, etc. The detailed expenditure information also allows construction of price measures as in Thacker and Wilson [2015]. I use this same price measure here, and include this in the model of the discrete choice decision process. Specifically, the variables used in this estimation procedure are age of the reference person, the number of individuals in the household, and alternative specific dummy variables.[10] Many of the CES variables, as mentioned, are defined for the reference person. This is the first person mentioned when respondents are asked who owns or leases the living space. Generally, this can be considered the head of the household. Summary statistics of key demographic variables from the final dataset are presented in Table 9.

[9] In estimation with these data, the no-telephone alternative is dropped. So few households choose no-telephone that including this low-cell-count choice does not add information, but detracts from the estimation of the other choice alternatives.

[10] In previous work (i.e. Thacker and Wilson [2015]), multiple specifications were considered and estimated, and the results were numerically similar and qualitatively equivalent.

TABLE 9. Variable Means by Choice

	Family Size	Age	Real Income	Married	Urban	Male
None	2.32	38.78	25.56	0.32	0.95	0.45
Land	2.40	50.66	35.13	0.49	0.88	0.51
Cell	2.28	36.99	36.85	0.35	0.95	0.52
Both	2.76	48.17	61.78	0.65	0.91	0.51

The data are available for years 1994 to 2012. Despite the category being included in the CES dating as far back as the 1980s, all entries in the cell phone expenditure category are zero prior to 1994. One of the strongest features of this dataset is the expansive time-period over which it has been collected. To this author's knowledge, the longest period of time covered by other datasets used in telephony research has been less than a decade. For a dynamic model of market evolution such as this one, this feature of the data is ideal. Although these data are for multiple households and over 19 years, it is not a true panel, in that many households appear only one time and none appear for more than 5 quarters. In total, I observe just over 296,000 individual choice occasions over the course of this 19-year period. Choice shares between telephony alternatives are presented in Table 10.

Results and Applications

The time-varying parameter, multinomial logit presented in Section 3.3 was estimated with the methodology presented in Section 3.4 and the data described in Section 3.5 using the University of Oregon's Applied Computational Instrument for Scientific Synthesis (ACISS).[11] In this estimation, included in the model are alternative specific dummy variables, price, age, and family size. Due to the low number of observations, the no-phone alternative was dropped from the analysis and those households choosing that alternative were removed from the data. Additional tables are

[11]See Appendix C for discussion of the computational burden of these methods.

TABLE 10. Consumer Choice Shares Over Time

Year	No Phone	Land Only	Cell Only	Both	Total	Land or Both	Cell or Both
1994	0.83	95.72	0.05	3.40	100.00	99.12	3.45
1995	0.78	92.18	0.09	6.95	100.00	99.13	7.04
1996	1.27	88.45	0.14	10.14	100.00	98.59	10.28
1997	1.34	84.85	0.12	13.69	100.00	98.54	13.81
1998	1.13	82.23	0.22	16.42	100.00	98.65	16.64
1999	1.21	78.56	0.25	19.99	100.00	98.55	20.24
2000	1.15	73.37	0.49	24.99	100.00	98.36	25.48
2001	0.62	60.72	1.07	37.58	100.00	98.31	38.66
2002	0.00	49.31	2.69	48.00	100.00	97.31	50.69
2003	0.00	47.74	4.71	47.55	100.00	95.29	52.26
2004	0.01	46.04	6.80	47.15	100.00	93.19	53.95
2005	0.02	41.69	9.24	49.05	100.00	90.74	58.30
2006	0.02	38.61	12.28	49.09	100.00	87.70	61.37
2007	0.13	32.23	16.38	51.26	100.00	83.50	67.64
2008	0.37	29.93	19.96	49.74	100.00	79.66	69.70
2009	0.27	27.31	23.84	48.59	100.00	75.90	72.42
2010	0.28	23.76	28.51	47.45	100.00	71.21	75.97
2011	0.32	22.88	33.12	43.68	100.00	66.56	76.80
2012	0.32	19.89	36.29	43.49	100.00	63.39	79.78
Overall	0.53	54.50	10.33	34.64	100.00	89.14	44.97

provided in the appendices of this paper; additional tables are provided in Appendix D.[12] Key results and the most important tables and figures are presented below.

Price Sensitivity

The prior distribution for the initial value of the coefficient on price is negative, so that it must be strictly negative. Through time, the coefficient on price decreases from a posterior median of -2.25 in 1994 to a posterior median of -16.6 in 2012. The increase in magnitude of this negative coefficient suggests that consumers' utilities become more sensitive to price through time. With an average price of service equal to approximately $42 for either single-choice alternative (i.e. not both), this points to the increasing

[12]Additional figures are available from the author by request.

importance of price. As may be expected, without consideration of price, most households would get the highest utility from the both alternative, especially by 2012. However, the considerable difference in cost for the both alternative is responsible for driving utility down in later years when households tend to choose cell phone only more frequently than other alternatives. This is captured by the increasing magnitude of the price coefficient. This is likely driven by the fact that cell phone services become more reliable through the sample, decreasing the need for landlines to have reliable telephone services in the home. This allows consumer households to be more sensitive to price because the products become more substitutable so that they do not require the most expensive alternative of selecting both services.

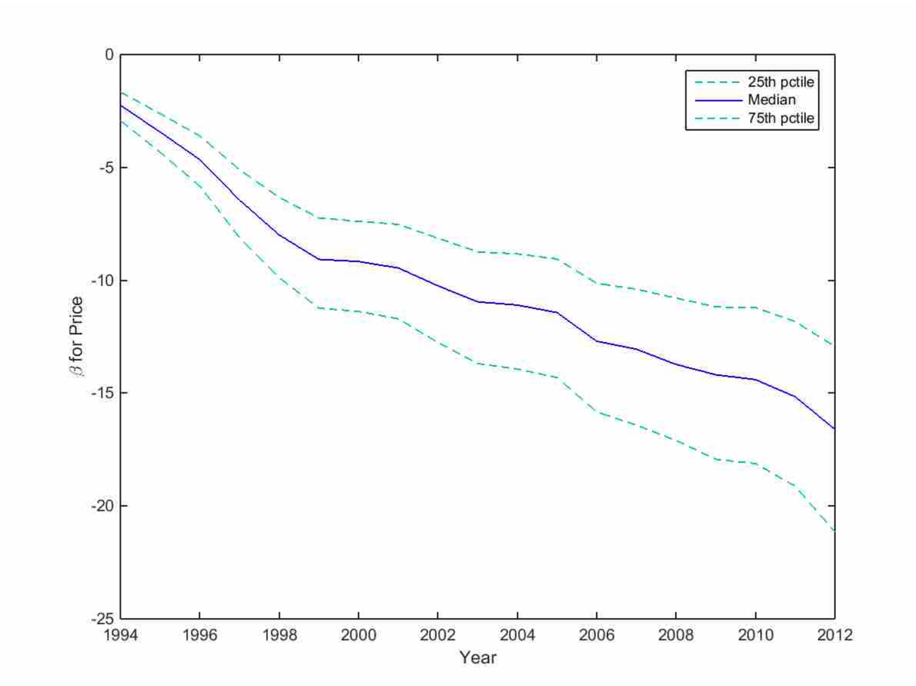
TABLE 11. Deterministic Utility for a Median Household

Alternative	(1)	(2)	(3)
Landline Only	0	0	0
Cell Only	-1543.7	160.37	78.09
Both	-618.329	386.153	56.353

To illustrate this point, consider the median household in these data: a household with two members and reference person aged 46 years old. The deterministic component of utility for each alternative is presented in Table 11 for this household under three different parameter specifications.[13] First are the median parameter estimates for 1994; the second are the median parameter estimates for 2012 except the coefficient on price, which remains at the 1994 estimate; the final column uses median estimates for 2012, including the price coefficient. Note that in 1994, virtually all households of this type choose landline. If non-price utility, i.e. the alternative-specific dummies and demographic-specific coefficients, changed in the same way that is observed but consumers' disutility

[13]Utility determines the choice probabilities according to the standard logit formula, $P(Y_{it} = j) = \frac{exp(U_{ijt})}{\sum_{m=1}^{J} exp(U_{imt})}$

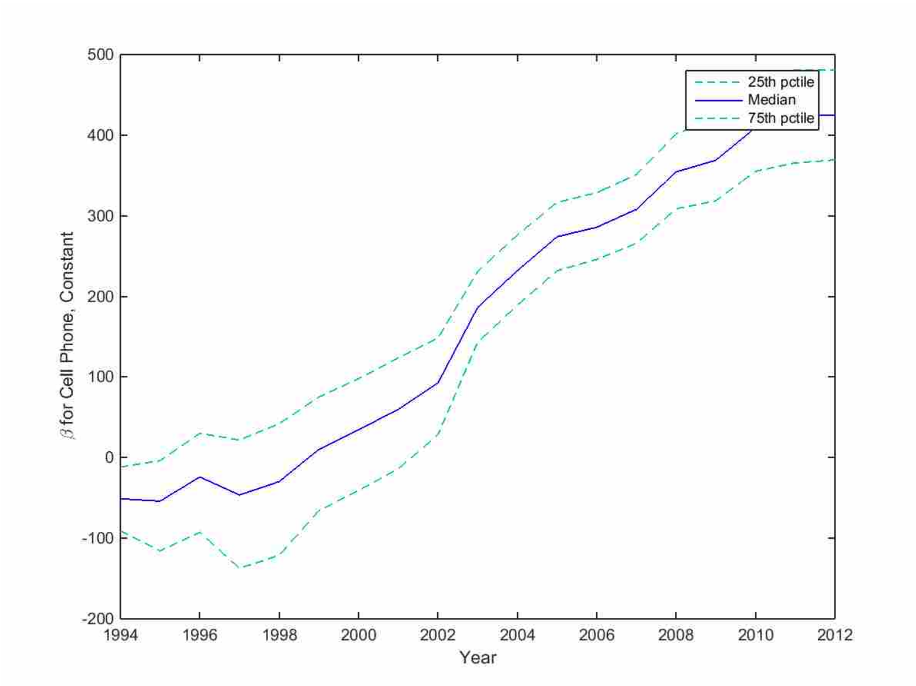
FIGURE 9. Price Coefficient Through Time



from price remained the same, virtually all households of this type would choose landlines as well as cell phones. When the price coefficient changes to be as it is estimated, this flips, and virtually all households of this type choose cell phone only. Thus, even though technological and cultural changes have been crucial for the adoption of cell phones, it is this increased disutility from price that drives households away from landlines, thereby providing an effective competitive constraint on landline pricing.

The posterior distribution suggests that random noise in the price coefficient's transition equation, rather than deterministic drift, is most supported by the data. That is, the increase in sensitivity to price through time is not deterministically driven in the transition equation. The running mean plots appear to level off around draw 40,000,

FIGURE 10. Cell Constant Coefficient Through Time



but they continue to move around to some degree. This is driven by the high level of autocorrelation between draws, which can be seen in the associated autocorrelation functions. For instance, the most dramatic, and unyielding autocorrelation is that of σ_{ω}^{price}, which is still above 0.4 at 4,000 lags. Even if convergence is reached, this correlation pulls the mean in different directions for short periods. Fortunately, as more draws are taken, the adaptive MH algorithm is able to minimize this effect through a more efficient proposal distribution; an adaptive proposal is exceptionally well suited to cases with many parameters for this reason.

Non-Price Parameters

Some parameters of the utility function do not appear to move substantially through time; however, the most striking movement of parameters is that of the alternative-specific dummy variables. For example, the coefficient on the cell-phone-only alternative-specific

TABLE 12. Posterior Distributions for β_t, 1994 and 2012

ALT.	VARIABLE	Year	5th-tile	25th-tile	Median	75th-tile	95th-tile	StdDev
	Price	1994	-3.87	-2.92	-2.25	-1.66	-1.13	0.63
		2012	-26.84	-21.15	-16.60	-12.93	-9.47	4.11
Cell	Constant	1994	-147.07	-90.63	-51.05	-11.73	31.61	39.45
		2012	309.64	369.27	424.68	480.66	539.00	55.69
Cell	Age	1994	-41.29	-34.74	-29.26	-23.90	-17.57	5.42
		2012	-4.09	-3.36	-2.75	-2.16	-1.58	0.60
Cell	Family Size	1994	-75.27	-47.04	-24.40	-1.60	22.25	22.72
		2012	-22.77	-15.82	-9.66	-3.39	3.29	6.21
Both	Constant	1994	38.12	58.89	82.09	103.88	124.77	22.49
		2012	574.55	731.57	900.57	1112.78	1385.08	190.61
Both	Age	1994	-3.33	-1.92	-0.85	-0.26	0.12	0.83
		2012	-1.89	-1.36	-0.90	-0.46	0.02	0.45
Both	Family Size	1994	-3.12	0.42	3.57	7.99	14.24	3.79
		2012	-9.97	-4.25	1.19	6.69	12.67	5.47

dummy variable starts off at -51.05, but increases through time to a posterior median of 424.68 by 2012. This points to increasing utility from the cell phone alternative relative to landline. In fact, this evolution and change in products and technology is one of the motivating ideas behind the development of this estimation procedure. A median value of 424.68 in 2012, up from -51.05 in 1994, represents results that are both empirically interesting and economically relevant. Relative to the magnitude of utility in these choice models, those values represent massive swings in utility for households from 1994 to 2012.

Now consider the coefficient on the alternative-specific dummy variable for the both alternative. Again there are economically significant changes through time. Indeed, the 5^{th} percentile of the posterior distribution for τ on this parameter is positive, and the median for this drift parameter is 53. Yet again, this points to the increasing utility of cell and landline phones relative to the landline-only alternative. The increasing technologies

FIGURE 11. Cell Age Coefficient Through Time

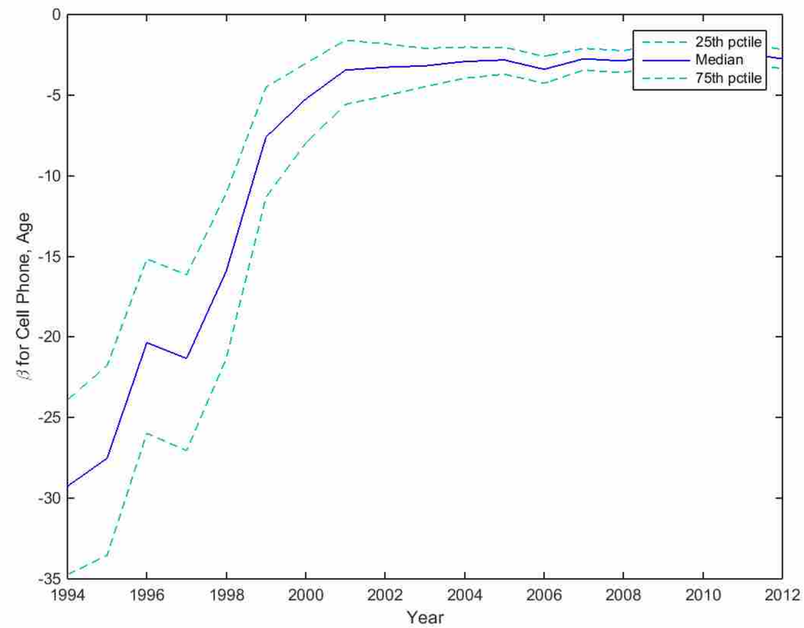
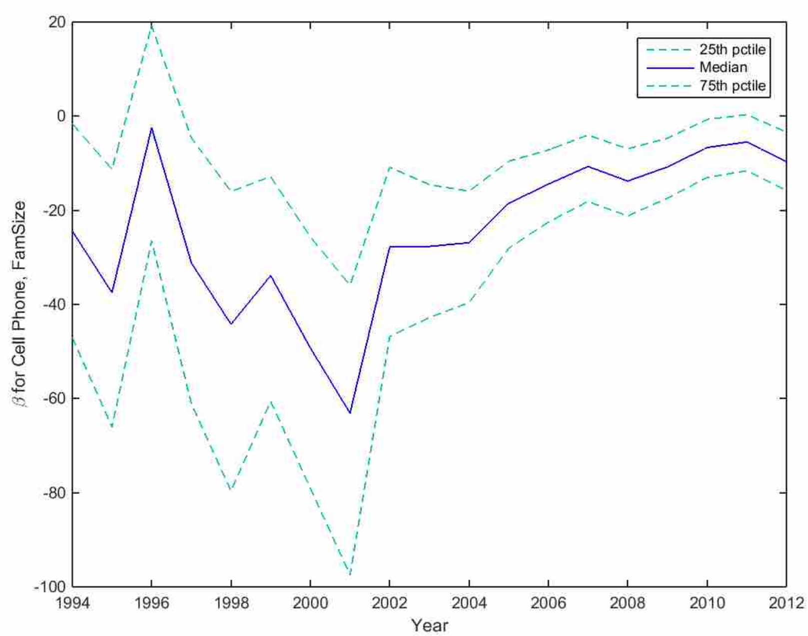


FIGURE 12. Cell Family Size Coefficient Through Time



and product-quality in the cell phone market are providing economically important utility gains to consumers whether or not a household has a landline telephone.

The remaining coefficients for the cell-only alternative move less substantially. For instance, the coefficient for age on the cell-only alternative increases from a median of -29 in 1994 to a median above -4 by 2001 and then remains fairly constant until the end of the sample. A negative coefficient on this variable implies decreased utility from cell phone relative to landline for older households. This is consistent with younger households being disposed to adopting new technology in earlier years, with this effect dissipating through time, but remaining present to a lesser magnitude through the rest of the sample. The oldest households, indeed, receive the highest relative utility from landline-only among otherwise equivalent households. Similarly, the coefficient on family size for the cell phone alternative is nearly constant through time, although the median is negative for all years in the sample. This points to larger households getting relatively more utility from the landline alternative than otherwise equivalent households. This is consistent with the notion that larger households receive more utility from a landline because more people can use a landline than a cell phone, which may travel with a single person in the household.[14] Also, the posterior distribution of drift, τ, for both of these parameters is mostly positive, pointing to a deterministic drift in the direction of diminishing these effects.

One interesting feature of this estimation procedure is the magnitude of variation in the posterior distribution through time. For instance, in the figures of cell-phone-alternative coefficients, the spread of the included central posterior intervals decreases

[14]This does not suggest that these households get more utility from landline only, but rather that these households receive less utility from cell phones, relative to landlines, than do smaller households.

FIGURE 13. Both Constant Coefficient Through Time

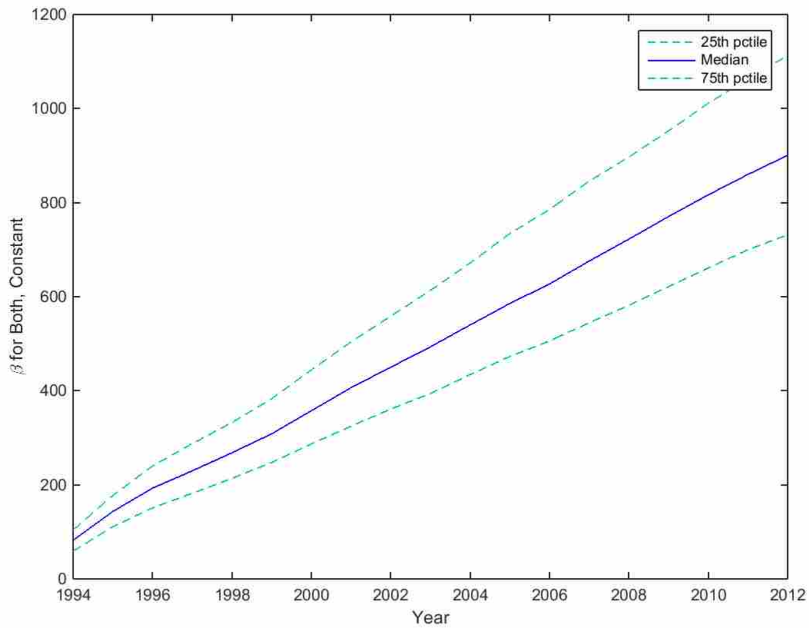


FIGURE 14. Both Age Coefficient Through Time

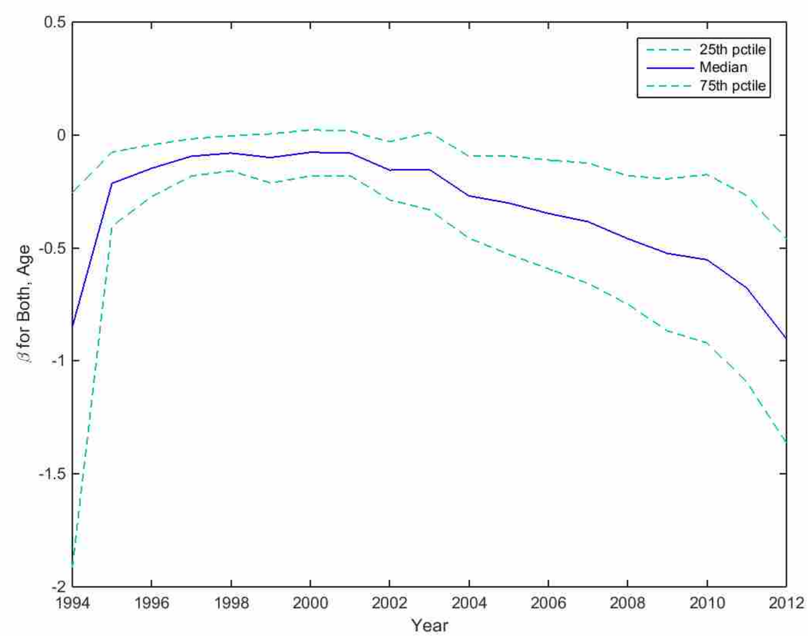
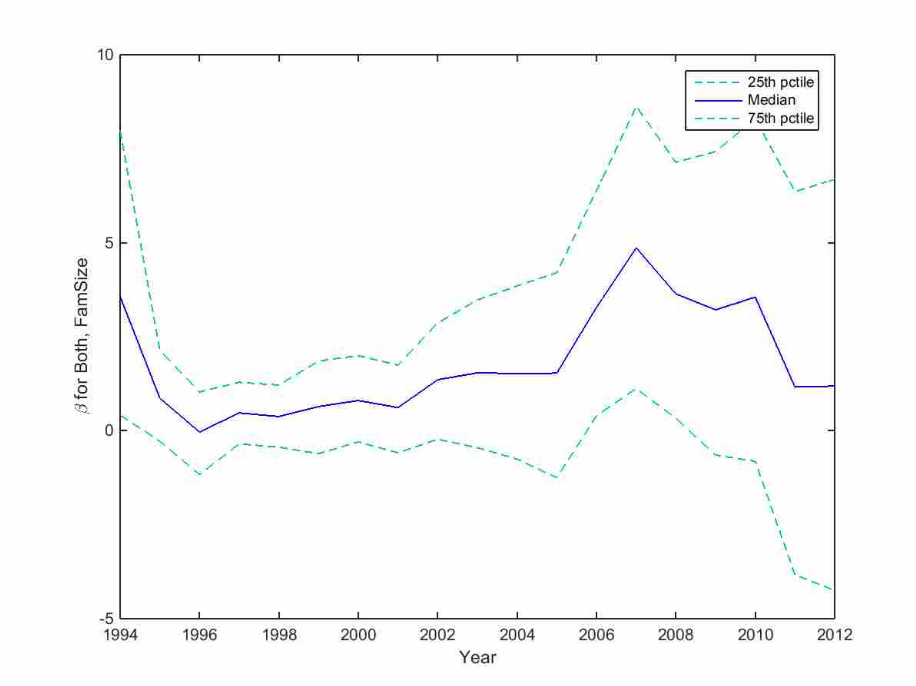


FIGURE 15. Both Family Size Coefficient Through Time



through time. This is driven by the relative frequency of households choosing this alternative at different periods of time. In early years, fewer households choose only cell phone, and so the data provide less certainty about the coefficients for that alternative. In terms of the posterior, which may be thought to represent our uncertainty about the value of the parameters, this emerges as larger posterior variance, which can be seen in the figures plotting parameters through time. Similarly, the number of households choosing the both alternative reaches its maximum near the center of the data, and so there is greater uncertainty for these coefficients toward the beginning and end than in the middle of the sample-period.

For the both alternative, the posterior median is negative in all years, but economically small relative to the alternative specific dummy variables, which play an economically significant role in household utility. Households of older consumers will receive less utility from the both alternative relative to landline than will younger households. Additionally, this effect is relatively constant through time. As with older versus younger households, the size of a household has economically small impact on utility for the both alternative relative to landline. The posterior median for the both alternative, family-size coefficient is positive for all years except 1996 when it is -0.035.

Model Comparison

One of the benefits of Bayesian estimation is a straightforward approach to comparing models. Specifically, Bayesian model comparison uses the marginal likelihood of each model to determine posterior model probabilities. These probabilities are generated by the following formula:

$$Pr(M_i|Y) = \frac{f(Y|M_i)Pr(M_i)}{\sum_{\upsilon=1}^{\Upsilon} f(Y|M_\upsilon)Pr(M_\upsilon)} \;\; \forall \;\; i = 1, \ldots, \Upsilon$$

where $Pr(M_i|Y)$ is the posterior model probability for the model denoted M_i given data denoted Y, $Pr(M_i)$ is the prior model probability, Υ is the number of models considered, and $f(Y|M_i)$ is the marginal likelihood, or the average fit of the model. While this technique can also be used for model averaging, I use it to determine whether a time-varying parameter specification better fits the data. While the random-walk time-varying parameter specification is more flexible, it is not the case that this approach necessarily chooses the more flexible model. Specifically, this approach penalizes a model with more parameters through the prior distributions; the prior distribution over a group of parameters has a lower average value when there are more parameters in that set. This penalty acts against this time-varying parameter specification because it has many more parameters, and so it is only preferred when the likelihood function is substantially higher.

This enters the posterior model probability through the marginal likelihood:

$$f(Y|M_i) = \int p(Y|\theta, M_i)p(\theta|M_i)d\theta$$

where θ denotes the parameters of the model and $p(Y|\theta)$ and $p(\theta)$ are the likelihood and prior probability distributions as in Section 3.4.

I use this framework to compare the specification of this paper to two other specifications. The first alternate specification has no consideration of time; parameters are constant, but utility is of the same form as the specification in this paper. The second alternate specification uses time trends; parameters are still constant, but in addition to the primary specification of utility in this paper, utility also has alternative-specific trend variables. To summarize:

$$\begin{aligned}
Y_{it} &= \underset{j \in J}{\operatorname{argmax}} \left\{ U_{ijt} = X_{it}\beta^X_{ijt} + Z_{jt}\beta^Z_{it} + \epsilon_{ijt} \right\} \\
\bar{\beta}_t &= \bar{\beta}_{t-1} + \bar{\tau} + \omega_t, \;\; \omega \sim N(0, \bar{\sigma}^2) && \text{(Model 1)} \\
Y_{it} &= \underset{j \in J}{\operatorname{argmax}} \left\{ U_{ijt} = X_{it}\beta^X_{ijt} + Z_{jt}\beta^Z_{it} + \epsilon_{ijt} \right\} \\
\bar{\beta}_t &= \bar{\beta}_{t-1} && \text{(Model 2)} \\
Y_{it} &= \underset{j \in J}{\operatorname{argmax}} \left\{ U_{ijt} = X_{it}\beta^X_{ijt} + Z_{jt}\beta^Z_{it} + YEAR_t\beta^{yr}_{ijt} + \epsilon_{ijt} \right\} \\
\bar{\beta}_t &= \bar{\beta}_{t-1} && \text{(Model 3)}
\end{aligned}$$

where $\bar{\beta}$ represents each parameter of the measurement equation.

TABLE 13. Model Comparison

	$Pr(M_i)$	$log(f(Y\|M_i))$	$Pr(M_i\|Y)$
Model 1	0.333	-18,055.711	1
Model 2	0.333	-160,498.511	0
Model 3	0.333	-111,332.896	0

The results are presented in Table 13. Given equal prior probability to each of the models, the posterior model probabilities favor the time-varying parameter specification by a large margin. In fact, given any reasonable prior distribution over the models, the marginal likelihoods are such that the posterior will virtually always favor the time-varying parameter specification.

Conclusion

This paper set out to study consumer choice through time in a market with tremendous change in the product space. To do so, I implement the random-utility framework and, specifically, the logit class of discrete choice models. With SMC filtering techniques, I extend this, and the broader class of discrete-choice models, to allow for time-varying parameters. Finally, I implement this model using data over a 19-year period, during which most of the adoption of cell phones took place.

This new estimation methodology along with the use of Bayesian econometric techniques, provides a variety of contributions to the literature. Foremost, these techniques allow for the inclusion of time-varying parameters in the wide class of models with latent dependent variables. As authors such as Engle [2014] have suggested, the assumption of constant parameter values is one that is rarely questioned; techniques that allow for such generalizations provide alternatives to this assumption. Bayesian techniques, in addition to providing useful tools such as inclusion of prior knowledge and model selection, allow estimation of the parameters of the measurement equation in each time-period. That is, with this estimation strategy, it is possible to estimate the parameters of discrete-choice models in every period when those parameters change in each of those periods.

Importantly, I have learned more about the motivating problem in addition to the methodological contribution. By allowing the parameters to vary randomly through time, I have estimated the transition equation, which governs the movement of the parameters.

In this way, it is clear that some of these parameters vary more randomly, while others have deterministic movement in the form of drift. This provides insight to forecasting future changes. For instance, the drift parameters of the transition equation for the coefficients on family size and age for the cell-only alternative point to decreased negative impact on utility from these household characteristics in the future. The strongest of these is, of course, the alternative-specific dummy variable for the both alternative capturing the increased utility through time from changes in technology. From a descriptive, rather than forecasting, perspective, this has also provided useful detail about the change in sensitivity to price in this market through time. For regulatory policy, this supports the argument that cell phones do provide an effective competitive constraint on price for landline services.

CHAPTER IV

A DYNAMIC MODEL OF OLIGOPOLISTIC COMPETITION WITH SUPPLY-SIDE LEARNING: COSTS AND COMPETITION IN THE US SMARTPHONE INDUSTRY

Introduction

Smartphones have transformed the way people communicate, and seem to pervade more aspects of people's lives all the time. The first true smartphone was BellSouth's Simon Personal Communicator (Sager [2012]), and smartphones took various forms until the introduction of Apple Inc.'s iPhone, released in July 2007. The iPhone was the first smartphone of the form most people are used to today, with a full touch-screen display, and a variety of features, including music, email, and of course, cellular phone calling (Apple, Inc. [2007]).

I investigate firm competition in the US smartphone industry, an industry with significant fixed costs and intellectual property in which firms release new devices frequently to remain at the forefront of available technology and consumer demand. For example, various versions of the ten iPhone models have been released over 12 unique release dates in a seven-year period (Apple, Inc. [2007]). As of this writing, four of the ten iPhone models remain in production while Samsung has released more than 20 individual Galaxy S-series devices in less than five years. Dates of device release and discontinuation are among the strategic dynamic decisions firms must make in order to compete in this market. Another feature of this market is that firms likely do not have perfect information about demand because the technology and product space changes and develops so rapidly. I focus my model around these features using a dynamic oligopoly model expanding on the seminal work of Ericson and Pakes [1995b]. Specifically, in each period of the dynamic game, firms decide whether to release or discontinue devices and how to price their device in the current period. In doing so, firms learn about demand and costs in the industry by forming rational expectations over the parameters of those functions similar to recursive least squares adaptive learning as in Evans and Honkapohja [2001]. Within each period, firms compete in a static, Bertrand-Nash pricing game of competition that I adapt from Berry et al. [1995] (henceforth, BLP) to incorporate this learning and incomplete information.

With this framework in place, I proceed with estimation adapting the empirical strategy of Bajari et al. [2007] (henceforth, BBL). That is, I estimate demand as a function of product attributes and unobserved characteristics, optimal policy functions for device release and discontinuation dates, costs of a new-product release, costs of production, entry cost, and scrap values. To accomplish this, I must estimate optimal policy functions for firms. With these in hand, I find market entry costs and market exit scrap values over $2 billion, device release costs over $100 million, and costs to continue offering a device model for sale equal to about $16 million. These substantial fixed costs are economically important with meaningful impact on the competitive environment. Using these results, I determine the strategic behavior of firms and the value of product attributes and advances to consumers.

The rest of this paper proceeds as follows. Section 4.2 presents industry background and recent literature related to the rest of this work in industry, theory, and empirical strategy. Section 4.3 presents my theoretical model of the industry and Section 4.4 presents the empirical strategy for estimation of the theoretical model. Finally, I introduce the data available for estimation in Section 4.5 and estimation results in Section 4.6 before concluding in Section 4.7.

Background

Smartphones are the combination of cellular telephones with a variety of other features, typically features previously found on Personal Data Assistants, or PDAs. The earliest of these was the BellSouth's Simon Personal Communicator released in 1994. This was followed by the rise of Research In Motion (RIM)'s BlackBerry devices, which were the market leaders in the United States for about a decade. The first device by RIM was available in 1996 and allowed users to send messages over the internet. By 1999, the first product under the BlackBerry name was released and could send and receive emails. This email client was even made available on other companies' devices.

In 2007, Apple released the original iPhone. This smartphone was the first of the modern design - a large touchscreen display that included a touchscreen keyboard and a variety of features including phone, SMS messaging, camera, email, iPod, and the full internet via Apple's Safari internet browser. Estimates of the cost to develop the original iPhone are as low as $150 million (Vogelstein [2008]), but others have cited the R&D budget of the company over the iPhone's development period being more than $2.6 billion, noting details revealed in a lawsuit in which Apple was suing Samsung for $2.5 billion (Bloomberg [2013]). The iPhone 3G came with the ability to access faster 3G network as well as the App Store. Apple's App Store allowed 3rd party developers to create and sell software for use on a smartphone, a feature that has proved extremely valuable to the consumers and companies alike (Kim [2012]).

Between 2007 and the present, wireless networks also improved from AT&T's edge network, to 3G, to 4G today. This network improvement, along with the technological improvement of the devices themselves, came with massive adoption through time. More than 250 million smarphones were sold worldwide in the year of 2010, and 28 percent of mobile phone users were using smartphones. Today this number is much greater; in the third quarter of 2014 alone, more than 335 million smartphones were sold worldwide.

Indeed, this industry has been well studied given its age. Cullen and Shcherbakov [2010] model consumer behavior in the cell phone industry focusing on switching costs between providers and the durability of devices themselves. The authors find significant evidence of switching costs at a dollar amount of $230 USD. Also focused on cell phone service providers, Zhu et al. [2011] investigate exclusive agreements between device manufacturers and carriers and the impact of these agreements on consumers. Here, the authors find that eliminating the exclusive contract of the iPhone with AT&T would have increased consumer welfare by $326 million. Sinkinson [2014] studies this relationship as well and focuses on the supply-side showing that Apple must have negotiated with competing carriers and AT&T had the highest willingness to pay for the exclusive agreement.

Network effects of different platforms have also played an important role in the market. Indeed, Luo [2015] finds that penetration of smartphones in the market would be 54.7% lower in the absence of these network effects. These primarily come from the operating systems; for example, when more consumers are using a given operating system, more third-party app developers will serve that operating system. Kim [2012] finds that Apple provided more benefit to consumers in terms of applications, but Google's Android system experienced higher sales due to better quality hardware when adjusted for price. Bresnahan et al. [2014] investigate the app developer market and find that, especially for those of the most well-used applications, developers prefer to supply their apps to multiple platforms rather than choosing just one. In addition to platform choice, device manufacturers can price discriminate by offering various products that are vertically differentiated. Fan and Yang [2014] study this price discrimination and consider how this situation compares to firms producing only their best product.

In my research, I use data from 2007 to 2014 to examine how firms make strategic, dynamic, profit-maximizing decisions. Specifically, I investigate the costs of entry and releasing new devices, when firms strategically release or discontinue devices, and how demand and costs change with product attributes in the highly competitive and evolving market. To accomplish this, I estimate a dynamic oligopoly model drawing from Ericson and Pakes [1995b] and Doraszelski and Pakes [2007] for a conceptual framework. I then implement the estimation methodology of BBL to obtain empirical estimates of the parameters of the model using the data. In order to utilize BBL, I extend BLP to estimate the unobserved state-variables. Various other work has used these methods to investigate other problems.[1]

Theoretical Model

The theoretical model I develop follows closely to Ericson and Pakes [1995b] and the related literature on empirical dynamic oligopoly models discussed in Section 4.2. There are two types of firms: (1) incumbent firms that compete in the market, and (2) potential entrants that may choose to enter. In each period, there are N_t incumbent firms, and ε potential entrants. Market demand is determined by the size of the market, M, and the value of the incumbents' devices to consumers relative to an outside option. Based on costs and demand, firms compete in Bertrand-Nash price competition in each period's device market conditional on the state of the industry. This equilibrium is a static Nash equilibrium in prices. However, between the static price competition, firms compete in a dynamic game in which they strategically release new devices and discontinue existing devices each period. Equilibrium in this game is a Markov Perfect Equilibrium in that equilibrium strategies depend only on the state of the industry, actions, and shocks in that period.

[1] See, for example Ryan [2012].

When making decisions, firms maximize the discounted sum of future profits. Profits are given by the profit function $\pi_i(s_t, a_{it}, a_{-it}, \nu_{it}(a_{it}))$; thus, firms seek to maximize the recursive value function:

$$V\left(s_t, a_t, \nu_{it}\left(a_{it}\right)\right) = \pi_i(s_t, a_{it}, a_{-it}, \nu_{it}(a_{it})) + E\left[\beta V\left(s_{t+1}, a_{t+1}, \nu_{it+1}\left(a_{it+1}\right)\right)\right]$$

where $V(\ )$ is the value function dependent on the state, actions, and cost shock, s_t is the vector of state variables in period t, a_t is the vector of actions by all firms in period t, a_{it} is the set of actions taken by firm i in period t, a_{-it} is the set of actions of all firms except firm i in period t, $\nu_{it}(a_{it})$ is the action-specific cost shock to firm i in period t for actions a_{it}, E denotes the expected value, and β is a common discount factor to all firms. Note that if firm i exits the market in period $\hat{t}$, the value function, $V(\cdot)$, will be equal to zero for each period $t > \hat{t}$. Also, in my model, the expectation, E, reflects not only the uncertainty due to random cost shocks as in previous literature, but also uncertainty because firms are learning about the industry through time as the product space evolves and more data become available. The evolution of the learned-demand state variables is uncertain, so supply-side learning is one source of uncertainty over which firms must form their expectations. Thus, firms form expectations over various sources of uncertainty.

Each period incumbents make multiple strategic decisions. Incumbents decide whether to release new devices, and if so, how many.[2] For each device released, firms incur a device-release cost, ϕ_r, associated with releasing that device. Incumbents also decide whether to discontinue each existing device in each period. If an incumbent discontinues all the devices it has on the market without releasing any new devices, it exits and

[2]For empirical tractability, I assume product attributes of released products are exogenous. This, along with research and development, is likely a fruitful area for future work.

recovers its scrap-value, ϕ_s. Releasing or discontinuing a device takes one period; these decisions do not take effect until the following period.[3]

Potential entrants also make strategic decisions deciding whether to enter, and if so, how many devices to release upon entry. To enter the market, an entrant must release at least one device. Entrants face new-device release cost, ϕ_r, but also face market-entry cost, ϕ_e. These costs are in addition to production costs. Finally, potential entrants are short lived and if one does not enter the market this period, it ceases to exist.

Following BBL, all firms competing in the device market choose a price each period to maximize single-period profits. This is set with a first-order profit-maximization condition, conditional on demand, the set of competing products, and costs. Demand is assumed to take the form of a logit model, such that the quantity demanded of a given product, Q_{jt}, is equal to

$$Q_{jt} = M \times \frac{exp(U_{jt})}{1 + \sum_{k=1}^{J_t} exp(U_{kt})}$$

where J_t is the number of devices in the market in period t, and U_{jt} is the value of product j to consumers in period t. Firms are assumed to face production marginal costs dependent on device attributes (e.g. screen size, processor speed), and per-period fixed costs per device on the market so that firm i's cost for device j in period t is given by

$$C_{ijt} = F + c_{jt} Q_{jt}$$

[3]Another possible area for future work is to investigate which firms are potential entrants, and whether those firms being short-lived is a realistic assumption. That is, it is not unusual to see firms in related industries enter this market rather than entirely new firms.

where F represents the per-period fixed costs per device,[4] and c_{jt} represents the per-unit marginal cost for device j. Firms also observe a cost shock, $\nu_{it}(a_{it})$, each period depending on what actions, a_{it}, they choose. They observe these shocks privately before making decisions. Thus, total production cost for firm i in period t is given by

$$C_t^i = \nu_{it}(a_{it}) + \sum_{j \,\in\, \Xi_{it}} C_{ijt}$$

where Ξ_{it} is the set of devices being produced by firm i in period t.

To this point, most of this model is in line with previous empirical dynamic oligopoly models. Inspired by Jovanovic [1982], I extend this literature by assuming that firms learn through time. Rather than the learning-by-doing style of learning (e.g. Jarmin [1994]), which may be more familiar in the industrial economics literature, I introduce an adaptive-learning framework in the style of Evans and Honkapohja [2001]. In doing so, I follow the learning literature from macroeconomics such that all firms are assumed to estimate demand as econometricians. Here, each firm implements BLP to estimate demand over the product space, then makes strategic decisions dependent on the estimated demand. Note that very recent work of Doraszelski et al. [2015] also brings adaptive learning to the industrial economics literature, and finds evidence of such learning in a newly formed industry of frequency response in the UK. I assume agents share a common beliefs about demand because BLP uses market-level data commonly known to all firms. Future work might consider Bayesian updating where firms are heterogeneous in their demand estimates through differing priors, which, at least in theory, may be estimated. Alternatively, each firm may only have industry data for the time-period over which that firm has been competing in the market; this would cause more senior firms to have

[4]It is theoretically possible to incorporate learning in this context as well such that F could be firm specific and depend on industry experience. I do not currently incorporate this feature, but this may be a fruitful area of work in the future.

superior knowledge and provide a flavor of learning-by-doing. I present these as interesting areas for future research, but proceed in this work as described above.

Demand is assumed to be constant. Preferences of consumers do not change; only the products change through time causing shifts in consumption and market shares. Although the firms' econometricians update their estimates each period to take advantage of more information, they assume that preferences over product attributes are constant over time.[5]

The timing of the model is as follows.

1. The period begins in a given state, s_t. This state includes the number of firms and devices in the market, as well as those devices' attributes, and estimated demand.

2. Firms draw private information. For incumbents this includes a scrap value, ϕ_s drawn from distribution $F_s(\cdot)$. For potential entrants, this includes a market-entry cost, ϕ_e drawn from distribution $F_e(\cdot)$. All firms in the period draw firm- and action-specific cost shocks, $\nu_{it}(a_{it})$.

3. Firms make strategic decisions simultaneously. Each entrant chooses whether to enter, and if so, how many devices to release. Each incumbent decides how many devices, if any, to release and discontinue. If an incumbent discontinues all devices, they exit the industry. Incumbent firms also choose prices for each device.

4. Firms compete in static, differentiated product, price competition to maximize single-period profits.[6]

5. The state, s_t is updated to s_{t+1} (e.g. new products are released, firms enter and exit, demand estimates are updated, etc.) and the next period begins.

This happens each period and firms compete with an infinite time-horizon.

[5] An oblivious equilibrium concept may also be useful where firms estimate demand for their product relative to the average product. This would simplify the simulation described in Section 4.4 because firms would not need to consider the evolution of different device attributes, only the evolution of the average device and number of devices. However, this would complicate the demand estimation because each firm would have its own estimates based on its own product. I proceed assuming shared beliefs about demand.

[6] This framework may also support dynamic pricing decisions, research and development, and advertising decisions, but I do not consider any of these here.

Estimation Strategy

I adapt BBL to estimate this dynamic oligopoly model using an adaptation of their two-step estimation strategy. In the first step, the econometrician estimates state-transition probabilities and policy functions, which leads to estimation of value functions by forward simulation. In the second step, the econometrician estimates the structural parameters of the model. This estimation strategy assumes that all state-variables are observed. In this case, there are state-variables that are unobserved to the econometrician, which previous literature has handled, but also state-variables that are unobserved to the firms themselves (e.g. demand). I develop a supply-side learning framework via iterative BLP to handle states unobserved to the firms as well as BLP to estimate unobserved state-variables that are unobserved to me, the econometrician, but are otherwise observed by the firms.

Unobserved State Variables

Since all state-variables are not observed, I begin by estimating the unobserved state-variables and treating these as observed proxies to the true state-variables.[7] The state includes costs, which are known to the firms, and demand, which firms learn about through time as more data become available. Thus, I first estimate the learned demand parameters at each point in time. I do this using BLP separately at each period, using data up to that period for estimation. In the last period, using all of the data in the sample and firms' first-order conditions, I estimate costs. Below, I introduce the framework of BLP.

I assume that demand follows the usual logit framework, such that consumers choose the alternatives that maximizes their utilities. Utility is modelled as a function of observed

[7]This is as suggested by BBL.

product attributes, X_j, prices, p_{jt}, demographic characteristics drawn from the population distribution, D_i, unobserved product specific attributes, ξ_j, and a random component, ϵ_{ijt}. Assuming a type-I extreme-value distribution of ϵ_{ijt} provides the usual logit framework. Firms are modeled as multi-product oligopolists that compete on price. BLP uses observed device characteristics, market shares, known market distributions of demographics, and market size to estimate demand parameters and costs. To do so, I implement the following procedure drawn from Nevo [2000].

1. Draw individuals labelled $i = 1, \ldots, \bar{I}$ from the population distribution. Each of these individuals is a set of demographics that enter the utility function.[8]

2. Given demand parameters of a given draw, θ, compute predicted probabilities for each person i, and average over these individuals to get predicted market shares, $\hat{S}(\theta)$.

3. Compute the mean level of utility from alternative j as δ_j using the contraption mapping $\delta_j^{h+1} = \delta_j^h + \log(S_j) - \log(\hat{S}(\theta))$ where S_j is the observed market share. Iterate this contraption mapping to convergence.

4. Solve for the unobserved product attributes by $\xi_j(\theta) = \delta_j - X_j\theta$.

5. Finally, I use this to estimate the parameters using GMM by:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}}\, G(\theta)$$
$$\text{where } \; G(\theta) = \xi(\theta)' Z \Phi^{-1} Z' \xi(\theta)$$

   where Z is a matrix of instruments and Φ is the weighting matrix.

[8]BLP also includes random coefficients. I also draw the random part of these coefficients here.

6. With demand parameters in hand, I use the firms' first order conditions to compute costs. In vector notation, the first order condition is given by

$$S - \Delta(p - mc) = 0 \quad \Longrightarrow \quad mc = p - \Delta^{-1} S$$

where Δ is the relevant set of own- and cross-price elasticities for a firm's products.

Transition Probabilities

Part of the first step of BBL is to estimate transition probabilities. For a small number of states, observed transitions can be used to estimate sample averages as transition probabilities. In this case, the state vector, s_t, includes the number of firms, the learned demand parameters, the number of devices as well as the attributes of each device. Thus, the space in which the states exist is not small enough to take this approach. Instead, I parameterize each state transition. Specifically, firms assume that the attributes of any phone on the market is constant from the time it is released to the time it is discontinued. Thus, there are no state transitions for these state variables. The number of firms and products evolves according to the firm entry and exit strategies. These are determined by the policy functions and cost shocks. As discussed below, this is sufficient for estimation to this point. The remaining issue is the distribution of cost shocks. This distribution is estimated from the policy functions derived in the next step and the observed transitions. This is sufficient to this point. As noted above, firms assume that they have the best estimates of demand, so that firms assume this state does not change through time when forming expectations, even though estimated demand will change through time in practice. This is for computational tractability, but could theoretically be relaxed.[9]

Finally, the attributes of new devices are the last states to be accounted for. I parameterize the state transitions of new-device attributes according to an autoregressive process. That is, for a new device, each attribute is assumed to be randomly drawn from a process according to the firm's existing products, or an industry average. Specifically, for continuous product attributes, the k^{th} attribute for product j released in period t, x_{jt}^k, is given by

$$x_{jt}^k = \begin{cases} \delta_i^k x_{j-1}^k + \varepsilon^k, & \text{if the firm is an incumbent} \\ \delta_e^k \tilde{x}_{t-1}^k + \varepsilon^k, & \text{if the firm is a new entrant} \end{cases}$$

where x_{j-1}^k is the median value of the product's k^{th} attribute among the firm's existing products, $\tilde{x}_{t-1}^k$ is the median value of the k^{th} attribute among devices released during the previous period, δ_i^k and δ_e^k are estimable parameters, and ε^k is a mean-zero random component with a variance to be estimated from observed device releases. For discrete product attributes, the k^{th} attribute for product j released in period t is given by

$$x_{jt}^k \sim \begin{cases} Pr\left(x_{jt}^k | x_{j-1}^k\right), & \text{if the firm is an incumbent} \\ Pr\left(x_{jt}^k | \tilde{x}_{t-1}^k\right), & \text{if the firm is a new entrant} \end{cases}$$

where the notation is the same as above for x_{j-1}^k and $\tilde{x}_{t-1}^k$, but here $Pr(\cdot)$ is a discrete probability distribution to be estimated from observed device releases, conditional on either the firm's most recent device-release or the previous-period industry median. This is also subject to reasonable attribute-specific restrictions. For example, the median device at the time of this writing would have the android operating system, but Apple would

[9]For example, we could estimate the change in demand parameters as a random walk and use this to define transition probabilities. This is computationally burdensome, so I treat these states as assumed constant, as described here.

never release a device without its iOS operating system. These informed restrictions are used in estimation.

Policy Functions

Optimal policy for each firm is a set of discrete choices. To my knowledge, methods from the existing literature (e.g. Hotz and Miller [1993] and BBL) allow for unordered, discrete strategic variables in the value-function context.[10] As shown in Hotz and Miller [1993], inverting choice probabilities for discrete variables gives relative value functions of actions where the optimal policy is to choose the argmax of the value functions. That is, for policy a_{it}, the firm's optimal policy function, $\sigma(s_t, a_{-it}, \nu_{it}(a_{it}))$, can be inferred from the value function, $v(s_t, a_t)$, such that

$$\sigma(s_t, a_{-it}, \nu_{it}(a_{it})) = a_{it} \iff v(s_t, a_{it}, a_{-it}) + \nu_{it}(a_{it}) \geq v(s_t, \bar{a}_{it}, a_{-it}) + \nu_{it}(\bar{a}_{it}) \; \forall \; \bar{a}_{it} \in A_{it}$$

where A_{it} is the set of possible actions, $v(\cdot)$ are the choice specific value functions, and $\nu(\cdot)$ are the choice specific cost shocks. Thus, using the observed data and a parameterization of $v(\cdot)$ as a function of the state, I am able to estimate the value function using a standard maximum likelihood logit approach for each of the strategic variables.[11] This provides the optimal policy function in a parametric form that can be used for any state.

Value Functions

The value function, $V(s_t, \sigma_t|\Theta)$, includes current-period profits plus the expected discounted sum of future profits. To form this expectation, BBL calls for the simulation of future states. Given the optimal policy functions estimated previously, I simulate a

[10] In general, there are two potential types of strategic variables: discrete and continuous. This model only uses dynamic strategic variables that are discrete.

[11] I assume that each of these decisions is independent.

large set of possible future states. This is done by assuming the earlier policy functions hold, generating random shocks for $\nu_{it}(a_{it})$, and solving for future profits in each of the forward-simulated periods. I then compute the discounted sum of future profits for each simulation, and, taking the average over this set of simulations, I find an estimate of the value function for each observed state and optimal policy. That is, I find an estimate of

$$V(s_t, \sigma_t | \Theta) = E\left[\sum_{\tau=t}^{\infty} \beta^{\tau-t} \pi(s_\tau, \sigma_\tau, \nu_{i\tau}; \Theta) \middle| s_t, \Theta\right] \tag{4.1}$$

where Θ are the structural parameters and s_t includes learned demand. This value function captures current-period profits, as well as the expected future profits based on the information that firms have at the time these expectations are formed. That is, this expectation can and will change as new information becomes available through the updated demand parameters as firms learn more about the market each period.

Completing estimation of the structural parameters using the minimum distance estimator of BBL requires evaluation of this value function repeatedly for different values of the structural parameters, Θ. In general, this requires simulation of the value function separately for each attempted value of Θ, which can be severly taxing in terms of computation. To get around this, BBL suggest using linearity of the profit function in Θ. That is, assume

$$\pi(s_t, a_t, \nu_{it}; \Theta) = \Psi(s_t, a_t, \nu_{it}) \cdot \Theta$$

where $\Psi(\cdot)$ is a vector of "basis functions". In this case, I can rewrite the value function as

$$V(s_t, \sigma_t | \Theta) = E\left[\sum_{\tau=t}^{\infty} \beta^{\tau-t} \Psi(s_\tau, \sigma_\tau, \nu_{i\tau}) \middle| s_t\right] \cdot \Theta \equiv W(s, \sigma) \cdot \Theta \tag{4.2}$$

where W is this expectation. With this form, I only need to compute the value of W once and can use that value for any Θ. I use this method here.

With a method for evaluating the value funtions, $V(\cdot)$, it is possible to estimate the structural parameters. Although a variety of estimation methods are available for this step, I implement a minimum distance estimator for the structural parameters. The idea is to find structural parameters that rationalize the policy functions estimated in the previous step.

The estimation method minimizes the squared sum of violations of the equilibrium conditions. That is, I search for parameter values that solve the following:

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} \sum_{i,s,\sigma_i'} \left(\min \left\{ V_i(s, \sigma_i, \sigma_{-i}|\Theta, \alpha) - V_i(s, \sigma_i', \sigma_{-i}|\Theta, \alpha), 0 \right\}^2 \right)$$

where σ_i' is an alternate strategy, and α is the set of parameters that parameterize the optimal policy functions. The minimum between the difference and zero is taken so that, if the difference is positive and does not represent a violation of the equilibrium conditions, this is not counted in the distance from an equilibrium. As such, the true value of the parameters, Θ_0, which represents an equilibrium of the model, would cause this distance to be minimized at zero, however this is not to be expected in practice due to the unobserved cost shocks.

To estimate this difference, I must also specify alternate strategies, σ_i'. Since there is an infinite number of alternate strategies (e.g. a firm could release any number of phones in a period), I use the sample equivalent of this minimum difference. The samples of σ_i' from the set of possible alternative strategies is drawn using $\sigma_i' = \sigma_i + \zeta$ where ζ is a random shock to the optimal policy function. Specifically, for binary discrete policies, the alternate strategy is simply the opposite action than was chosen.

Simulation for this procedure can be significant in terms of computation. To avoid this, I can use the linearity of the profit function in Θ as described in section 4.4. Then, forward simulation must still be done separately for each (i, s, σ_i') triple for consistency and unbiasedness of the estimator. However, I can reuse these simulations for each draw of Θ. Thus, as was explained above, evaluation of the value functions can be accomplished with one round of forward simulation, then a dot-product of the vector of basis functions, W, and the guess at structural parameters, Θ. Specifically, W includes the expected discounted sum of future devices released, market exit, and devices produced per period, as well as random shocks to estimate the distribution of these costs.

Data

The data for this project come from International Data Corporation's Mobile Phone Tracker.[12] These data track cell phones sold in the US over a seven-year period from 2007 until the third quarter of 2014 on a quarterly time-series; this provides 31 time-periods for estimation. Included in these data are the vendor, network interface (e.g. 4G FD-LTE), processor vendor, cores, and speed, camera quality, screen size, operating system and much more. Importantly, in addition to these included features, the data include average selling price and sales volume in various measures (units, dollars, and shipments). These data, in tandem with the theory presented in section 4.3, can be used to implement the estimation strategy developed in section 4.4. This paper makes use of all devices identified as "smartphones", which the International Data Corporation's Mobile Phone Tracker defines as devices that "contain a high level operating system" such as Android or iOS, that allow "Third-party appplications . . . to be natively installed". (idc)

Variables included in estimation include the following: Android, iOS, Windows, and Other OS are indicator variables indicating that a particular device uses the respective

[12]The author gratefully acknowledges funding for this data generously provided by the University of Oregon Department of Economics.

operating system where the reference group is the BlackBerry operating system.[13] 3G and 4G are indicator variables for whether a phone has the ability to use 3G and 4G wireless telecommunications networks, respectively. 16GB and 64GB are indicator variables indicating whether a phone has more than 16 GB but less than 64 GB of memory, or more than 64 GB of memory, respectively. Camera indicates whether the smartphone has a camera. Full Screen, Slider, and OtherForm all indicate the form factor of the phone where the messenger form factor is the reference group. The standard smartphone in today's world would be considered a full screen. TSR is the time since release, or the age of the specific device model in quarters. Prices are the average selling price of a device as reported in the data. These prices are the average street price of the specific device model in that quarter.

In estimating demand, I also make use of demographic variables drawn from the population distribution: age and college. Age is the age of an individual in years. College is an indicator variable for whether an individual has completed a college degree. I obtained demographic information from the IPUMS database. (Ruggles et al. [2010]) These data are then used to draw individuals from the population to identify various demand parameters.

As can be seen in Figure 16, smartphone sales have increased significantly over the past decade. With less than five-million individual devices sold in the first quarter of 2007, there has been an order-of-magnitude increase with over 40 million devices sold in the third quarter of 2014. The data also show that sales have become more seasonal over time. The increased sales have created a very large technology market for smartphones. This market has been, and continues to be, dominated by a few large firms. Figure 17 shows the number of firms of various sizes by total device sales over the sample time period

[13]Note that there are no Apple phones without iOS and no iOS phones made by any firm other than Apple; any identification related to this variable cannot separate effects of the operating system itself from effects of other Apple indiosyncracies.

FIGURE 16. US Quarterly Smartphone Sales

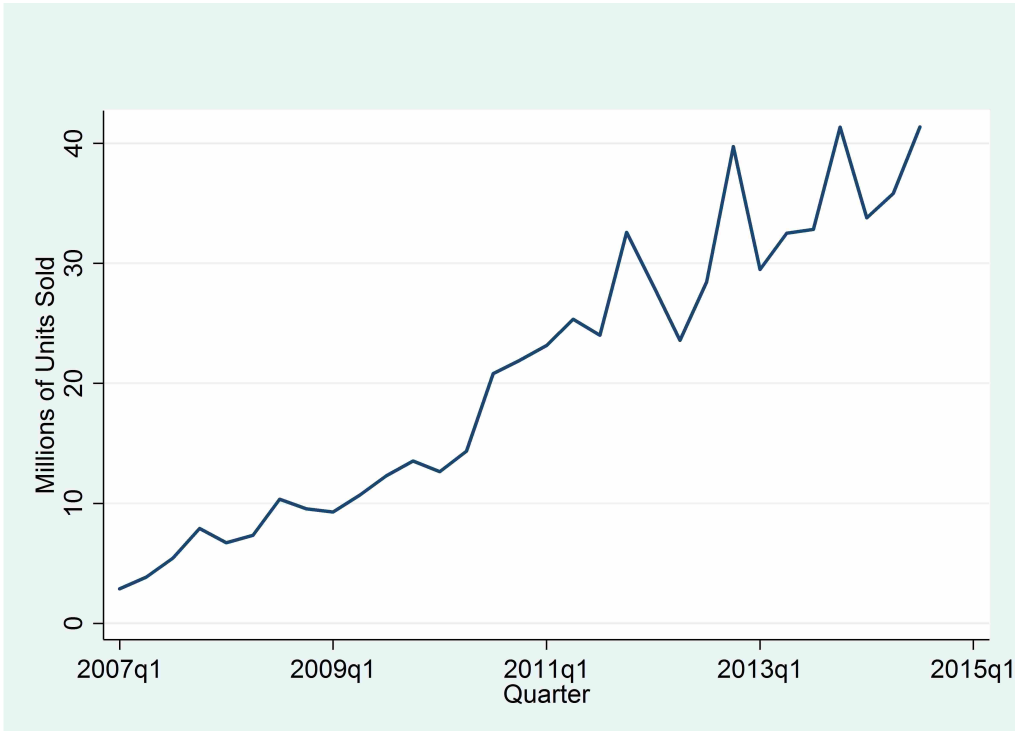
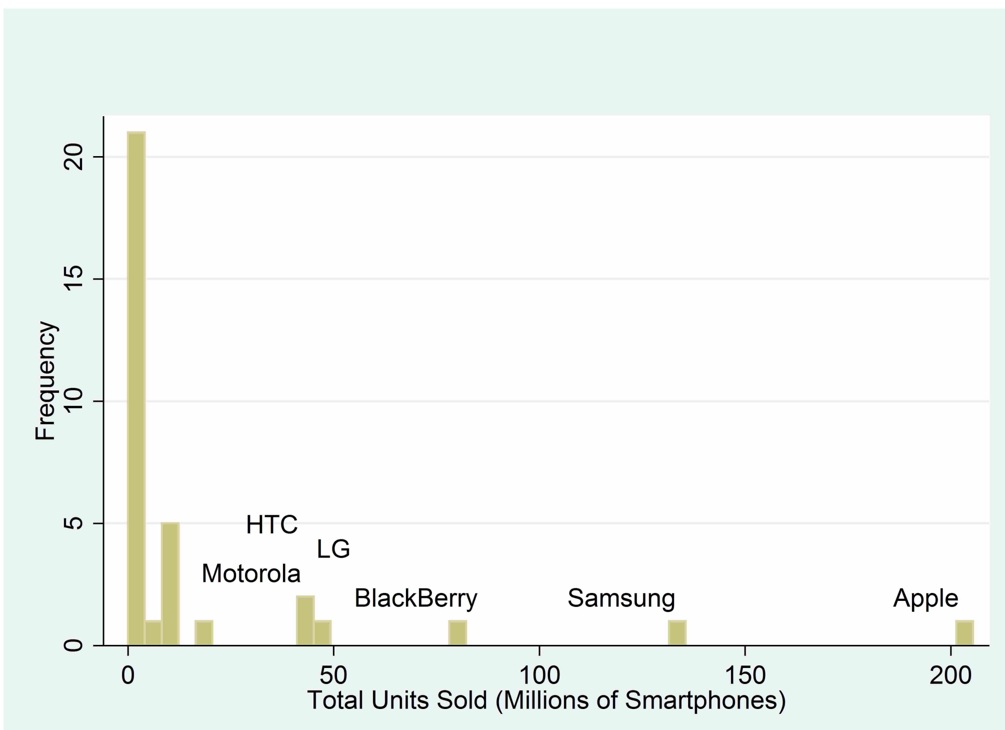


FIGURE 17. Distribution of Firm Size



in the US. Apple has the largest share during this period with more than 200 million smartphones sold, while only two other firms have more than one fourth of that amount, those being Samsung and BlackBerry.

In addition to well-documented changes in the devices and technology themselves, the firms that produce those devices have also changed. While BlackBerry is third in overall unit sales during the sample period, their market share has fallen dramatically as the overall size of the market has grown. Figure 18 shows the market shares of at-times-dominant firms through time. In 2007, BlackBerry held as much as 50% of the total unit sales of smartphones, but that market share has fallen since 2009 to nearly zero by the end of the sample. BlackBerry's fall coincided with the rise of the modern dominant firms: Apple and Samsung each hold over 20% of unit sales in each quarter over the final four years of the sample period. This distribution of market shares represents a related split in the operating systems being used in smartphones being purchased. Figure 19 shows the distribution of various operating systems through time. In 2008, Google, Inc.'s Android operating system did not yet exist. By the end of the sample period, Android came to dominate the smartphone market with 63.45% of all devices sold running Android. Android is an open-source software platform used by multiple device manufacturing firms including Samsung, LG, and HTC.

These data are extremely rich, and to my knowledge, have not been used to study the smartphone market in the literature, allowing for a new examination of the industry. The dataset is collected from shipments of new mobile phones from vendors. These are not, then, double counted when shipped between other levels of the distribution network. In the case where devices are shipped through different countries, they are only counted in the country of final sale; in this case, this is the US market. Products used by the device manufacturers themselves are also counted in shipments as are products donated or given away.

FIGURE 18. Smartphone-Vendor Quarterly US Market Shares

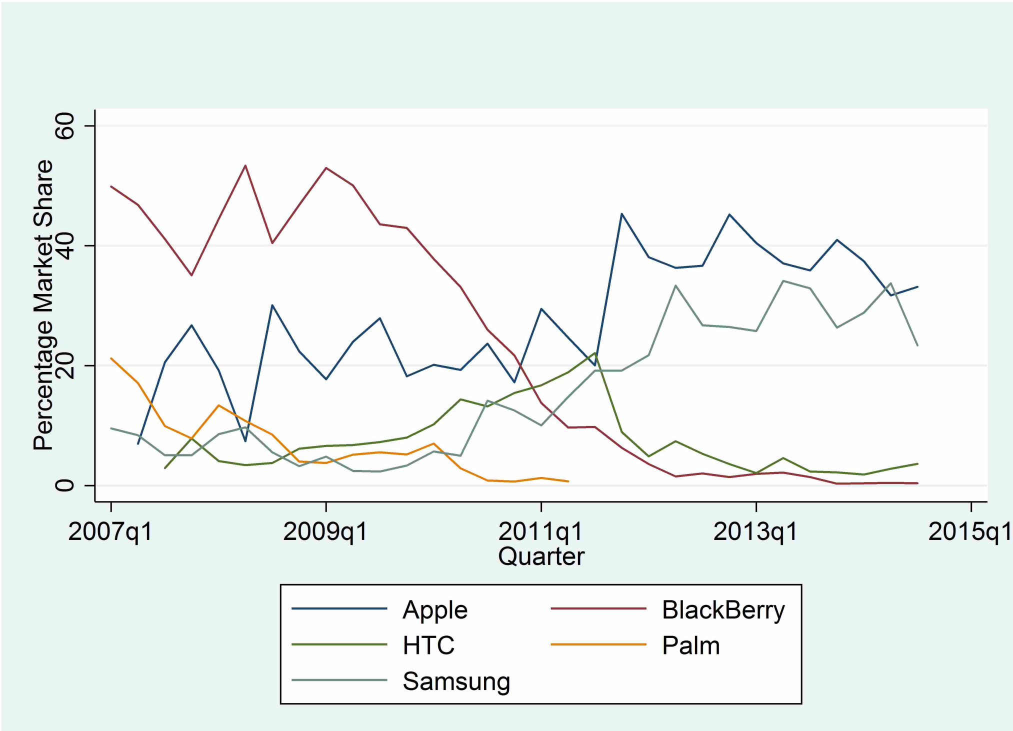
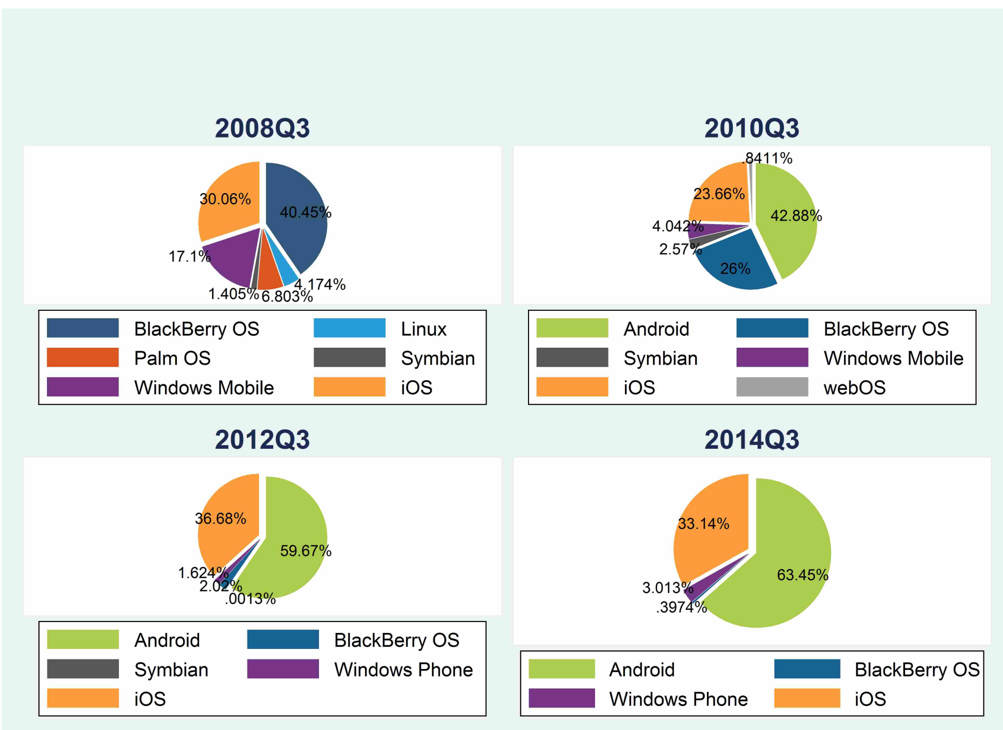


FIGURE 19. US Mobile OS Market Shares



Results

In this section, I present the results from estimation of the model presented in Section 4.3 using the estimation techniques and data presented in Sections 4.4 and 4.5, respectively. Standard errors are produced by bootstrapping the estimation routine. I begin with presentation of the structural parameters, which are the final results of the estimation routine. I then present results from the intermediate estimation steps including the learned demand coefficients and marginal cost estimates obtained through BLP, optimal policy-function and transition probability estimates used for forward simulation.

Structural Parameter Estimates

The end result of the estimation for which results are presented here, are the structural parameter estimates of the model. These include the device release costs, ϕ_r, market entry costs, ϕ_e, scrap values, ϕ_s, and per-period fixed costs, F. These results are presented in Table 14. First, consider the device release cost. This is the cost associated with developing and releasing a new product to the market. ϕ_r is a random variable that firms observe prior to making the decision to release or not release a device. It is drawn from a normal distribution with a mean of \$117 million and a standard deviation of \$4.6 million. This is an economically significant cost that reflects the substantial R&D costs associated with product development as well as advertising and other adminstrative costs. Even more significant is the market-entry cost, again observed by the firm prior to their entry in the market. A firm entering the market must pay this cost to begin competing in the smartphone market. This cost was estimated to have a mean value of \$2.68 billion and a standard deviation of \$46 million. This is an economically significant cost to market entry, and indeed, in line with some estimates of Apple's research and development costs associated with "Project Purple" to develop the original iPhone (Bloomberg [2013]). Each firm must pay the advertising and administrative costs of entering the market, but also the costs of aquiring the requisite technologies.

TABLE 14. Structural Parameter Estimates

Variable	Estimate (millions)
Model Release Cost Mean	117.4 ***
	(18.47)
Model Release Std Dev	4.572 ***
	(0.1223)
Entry Cost Mean	2682 ***
	(975.5)
Entry Cost Std Dev	46.11 ***
	(2.304)
Scrap Value Mean	2489 ***
	(697.8)
Scrap Value Std Dev	65.30 ***
	(28.04)
Model Offered Cost	15.78 ***
	(3.039)

In addition to costs associated with entering the market and releasing new devices, I have also estimated the value of market exit. The scrap value is observed by the firm at the beginning of the period, and after observing this value, firms can choose whether to discontinue their remaining devices and exit the market. This number is almost identically large to the market entry cost on the order of about $2.49 billion with a standard deviation of $65 million. The fact that these numbers are similar may point to the fact that failing or closing firms are often purchased by other firms.[14] Finally, in addition to these random costs of entry, exit, and new-device release, there are also per-period fixed costs, F, associated with offering a model each period it is available. This cost is estimated at $16 million and is equal for all firms and all devices. This cost primarily reflects the costs associated with selling a product model as separate from others such as keeping inventory and advertising.

[14]For example, see the purchase of Motorola Mobility by Google in 2011 (Google, Inc. [2011]).

Learned Demand and Marginal Cost Estimates

At each period in time, firms are assumed to learn demand as econometricians. The workhorse empirical method for random-coefficient demand models over the last two decades has been BLP, and as such, it is reasonable to assume that econometricians inside these firms are estimating demand according to those models. This method is implemented in each period using data up until that period to simulate what firms have learned about demand. Results for this process are presented in Table 15 for estimates as of quarter 1 in 2010, 2012, and 2014, as well as the last quarter of the sample period, quarter 3 of 2014. The included variables are Android, iOS, 4G, large Memory, Camera, Full Screen, OtherForm, TSR, Price, and a constant. TSR, price, operating system, and camera coefficients are random and also vary according to the age and education of individuals.

TABLE 15. Learned Demand Over Time

	2010Q1	2012Q1	2014Q1	2014Q3
Other OS	-2.084 **	-1.785 ***	-1.608 ***	-1.586 ***
	(1.053)	(0.04845)	(0.2442)	(0.1990)
3G	-0.3487 ***	-0.1528 ***	-0.1117 ***	-0.1068 ***
	(0.0005679)	(0.0002761)	(0.03006)	(0.002269)
4G		-0.3765 ***	0.02549 ***	0.1716 ***
		(0.1265)	(0.0009100)	(0.02053)
16GB	-0.9654 ***	-0.8622 ***	-0.5135 ***	-0.9306 ***
	(0.1841)	(0.3320)	(0.05101)	(0.3487)
64GB		0.2329 ***	-1.343 ***	-2.453 ***
		(0.004886)	(0.3395)	(0.01441)
Full Screen	0.3253 ***	-0.2020 ***	-0.2677 ***	-0.2476 ***

	(0.01852)	(0.009293)	(0.02344)	(0.07831)
Slider	-0.5069 ***	-0.6727 **	-0.6406 ***	-0.6846 ***
	(0.006906)	(0.3255)	(0.04512)	(0.01413)
OtherForm	-0.9315 ***	-0.7589 ***	-0.6679 ***	-0.6679 ***
	(0.1491)	(0.2269)	(0.05493)	(0.2375)
TSR	0.04620 ***	-0.4298 ***	-0.4277 ***	-0.4821 **
	(0.006262)	(0.07216)	(0.01139)	(0.2433)
TSR Std Dev	-0.05586 ***	0.06439 ***	-0.001782 **	0.0001064 ***
	(0.01895)	(0.003112)	(0.0008310)	(0.000004306)
TSR#Age	0.002279 *	0.01069 *	0.009315 *	0.01393 ***
	(0.001186)	(0.006067)	(0.005179)	(0.004636)
TSR#College	-0.001212 ***	0.006353 **	0.0001184 ***	-0.00009737 ***
	(0.00008027)	(0.003014)	(0.00003179)	(0.000002845)
Price	-0.0009647 ***	0.001193 *	0.008388 **	-0.001808 ***
	(0.0001223)	(0.0006496)	(0.003958)	(0.0002789)
Price Std Dev	0.0004397 ***	0.001104 ***	-0.001961 ***	0.0002295 ***
	(0.00006159)	(0.00009480)	(0.0001958)	(0.00005407)
Price#Age	0.0003659 ***	0.0001577 *	-0.0001213 *	0.0001679 ***
	(0.0001048)	(0.00008451)	(0.00006287)	(0.00005478)
Price#College	-3.872 ***	-0.1435 ***	0.002594 ***	0.002559 ***
	(1.404)	(0.003644)	(0.0001420)	(0.0001350)
Android	-0.1814 **	-2.595 ***	0.1321 ***	0.7170 ***
	(0.08800)	(0.7358)	(0.03865)	(0.1731)
Android Std Dev	-0.002988 **	-0.007888 ***	0.0004274 ***	0.000008114 ***
	(0.001244)	(0.0007819)	(0.00003803)	(0.000001191)
Android#Age	0.05589 ***	0.08150 **	0.01170 ***	-0.001281 ***

	(0.003974)	(0.03517)	(0.001285)	(0.00004749)
Android#College	-0.001859 ***	-0.002415 ***	-0.00001470 ***	-0.00002546 ***
	(0.00007502)	(0.0004347)	(0.000001182)	(0.000004082)
iOS	-1.048 *	0.8792 *	1.442 ***	1.703 ***
	(0.5471)	(0.4672)	(0.1417)	(0.1664)
iOS Std Dev	-0.0006782 ***	-0.002394 ***	-0.00001673 ***	-0.000004590 ***
	(0.000004679)	(0.0001141)	(0.000003035)	(0.0000006562)
iOS#Age	0.05482 ***	0.007097 ***	0.004496 ***	-0.0007571 **
	(0.01506)	(0.0007915)	(0.0007234)	(0.0003074)
iOS#College	0.0002844 ***	-0.002978 ***	0.00002244 ***	-0.000006527 ***
	(0.00008360)	(0.0004579)	(0.000001752)	(0.000002398)
Windows		0.1833 **	-0.2405 ***	-0.05777 ***
		(0.08118)	(0.06353)	(0.01391)
Windows Std Dev		0.001062 ***	0.00006758	-0.000004649 ***
		(0.00006113)	(0.00004497)	(0.0000007554)
Windows#Age		-0.02029 ***	0.001933 ***	-0.0004338 ***
		(0.007047)	(0.0002969)	(0.0001020)
Windows#College		-0.0001077 ***	0.00001344 ***	-0.000001095 ***
		(0.000003521)	(0.0000002924)	(0.0000002938)
Camera	13.83 ***	7.131 ***	0.6947 ***	0.7987 ***
	(4.347)	(1.982)	(0.1339)	(0.1048)
Camera Std Dev	0.07440 ***	-0.02245 **	0.0003334 ***	-0.00001489 ***
	(0.003004)	(0.009495)	(0.0001246)	(0.000001182)
Camera#Age	-0.2826 ***	-0.1115 ***	0.002301 ***	-0.001357 **
	(0.03253)	(0.02987)	(0.0005525)	(0.0005951)
Camera#College	-0.007833 ***	0.001917 ***	0.00001647 ***	-0.00002458 ***

	(0.002652)	(0.00009174)	(0.000002014)	(0.000004257)
Constant	-11.63 ***	-7.000 ***	-4.109 ***	-4.573 ***
	(2.770)	(2.051)	(1.060)	(1.750)

Time since release (TSR) is estimated to have a small, but positive impact on demand in early periods, but this effect is estimated as negative when more data become available. This points to consumers' preference for newer devices over older devices; in line with the findings of Thacker and Wilson [2015], younger people have more interest in newer technologies than older people, all else equal. The price coefficient is estimated to have a non-random component that is negative when using all of the data. However, this is not the case in 2014, quarter 1; further, the effect of age on the price coefficient is enough such that most consumers would have decreased utility from higher prices.[15] Also note that the constant in this utility function is negative. This points towards a preference for the outside option relative to purchasing a new device. Since most consumers purchase a phone approximately every two years, and the specified market size for each quarter is 25% of the US population, most consumers in the market will not choose to buy a new phone, so that the outside option receives a large share of the market.[16]

Among the remaining results, consumers prefer the Android and iOS operating systems over the alternatives. This likely explains why there has been a shift by producers towards the open-source Android operating system over their own software. Additionally,

[15] With a different distributional assumption on the random part of the coefficient such that it must be either positive or negative for all consumers, I expect that this coefficient may be economically more significant.

[16] One important aspect to this consumer decision is the outside option. For those consumers who have the "top-of-the-line" device, the outside option is much more attractive than for those consumers who do not yet own a device. This is one direction for future work in this area.

these likely reflect the network effects associated with operating systems and their third-party applications. Across all periods, consumers prefer phones with cameras to phones without cameras. The results are not consistent across periods as to whether consumers like phones with more memory.

TABLE 16. Marginal Cost Estimates

Variable	Estimate
Android	-0.3538 **
	(0.1471)
iOS	0.2030 ***
	(0.04487)
Windows	-0.2506 ***
	(0.0006505)
OtherOS	0.05418
	(0.03627)
3G	0.005978 *
	(0.003469)
4G	0.2512 **
	(0.09810)
16GB	0.4812 ***
	(0.1853)
64GB	0.5927 ***
	(0.2288)
Camera	-0.1129 **
	(0.04726)
Full Screen	-0.1910 ***
	(0.06696)
Slider	0.1415 **
	(0.06360)
Other Form	-0.07143 ***
	(0.005780)
Constant	5.987 *
	(3.285)

These last attributes are also those that largely impact production costs. Using BLP, I also uncover the marginal costs of production according to the following marginal cost function:

$$log(mc) = w\gamma + \omega$$

where w are the attributes of the phone and γ are the associated marginal-cost coefficients. All else zero, the cost of producing the marginal device is $398.06. This is made cheaper by using the Android operating system rather than developing a firm's own software; specifically, marginal costs are approximately 35% lower when using the Android software. These are significant cost savings over the alternative. Note that while the iOS variable is named for the operating system, the variation in the data does not allow separate identification of the costs associated with the iOS operating system from the other costs that are specific to Apple, Inc. devices. Finally, note that phones with 4G service and more memory are more costly to produce, while phones of the full screen form-factor are actually cheaper to produce.

Policy Function

In order to estimate the structural parameters of the model, it is necessary to simulate the future of the market to estimate the discounted sum of future profits for a firm given the strategies that they choose in the current period. These value functions are then used to uncover the relative values of the structural parameters using equilibrium conditions of the model. To simulate the future, it is necessary to simulate firms' actions in the future based on the future state of the market. This is achieved with the estimation of policy functions as presented in Table 17. The three columns represent the estimated policy functions for the three dynamic strategic decisions a firm must make in each period. The entry column presents the policy function of potential entrants. This is a binary logit with which firms choose whether to enter the smartphone market. There are 10 potential entrants in each quarter, and most choose not enter, hence the negative constant coefficient. The other explanatory variable is the firm's predicted market share were it to be competing with a product in the current period. This is generated using the transition probabilities for product characteristics presented in the following subsection as well as the learned demand up to the current period. This coefficient is negative, but not statistically significant, pointing to statistically zero impact of the firms' predicted market share on its decision to enter the market. While this is somewhat counter-intuitive, this only bolsters the idea that firms are not myopic, but rather focus on profits in the long-run.

TABLE 17. Firm Policy Function Estimates

	Entry	Release	Discontinue
Constant	-14.77 ***	0.5678 ***	-1.335
	(1.181)	(0.02035)	(0.8332)
Predicted Market Share	-0.06466		
	(0.2450)		
Product Market Share		1.123 **	9.952 ***
		(0.4728)	(1.309)
Other Share		-2.250 ***	-0.8657 **
		(0.6152)	(0.3826)
Product#Other Market Share		0.03566 ***	-89.34 ***
		(0.001798)	(33.56)

Incumbent firms have a different decision to make, and therefore, different policy functions. The first is the decision to release a new device. The firm decides whether to release a new device in the following period based on a binary logit with explanatory variables as follows: the predicted market share of a released device generated using the transition probabilities for product characteristics presented in the following subsection, the predicted market share of all other devices produced by the same firm in the absence of this could-be-released device, and the product of these two variables. The results show that the probability that a firm releases a new product is increasing in that product's predicted market share, but decreasing in the market share of the firm's other products. The larger the market share of the firm's other products, the more a new product cannibalizes the firm's own-product market shares as opposed to market shares of other firms, and the more likely that firm will choose to not release a new device. This also depends on the relative values of these variables through their cross-product, but this effect is economically insignificant.[17] Finally, the incumbent firms also decide whether to discontinue the production of their existing device models. Firms are less likely to discontinue a device, the larger the market share of the firm's other devices. This may point to larger firms producing a larger variety of products; while the coefficient on the device's own market share is positive, it is closer to zero, if not negative, when the cross-product coefficient is also considered. For the largest firms, a device with a small market share is much more likely to be discontinued, but firms with few other products are less likely be influenced in this decision by a lower market share.

New Products' Attributes and Transition Probabilities

The final part of the estimation routine to be presented is the estimation of transition probabilities. Most the state variables, such as the number of firms and devices, are determined by the optimal policy functions of the firms; however, the product attributes of newly released devices are taken as exogenous in this model. The model for the attributes of new device models are determined either by ordinary least squares for continuous variables or by logit for discrete variables. For incumbent firms, attributes of new products are determined by a constant and the median of that product attribute within the firm. For new entrants, attributes of new products are determined by a constant and the median of that product attribute over the entire market.

Note that for most of the discrete variables, the coefficient on the market median value is positive. This points to new entrant devices following the market rather than

[17] Note that the value of the cross-product variable is quite small given that both variables are less than one, and most are below 0.001.

moving away from the market median, as might have been expected if a firm entered with the intention of offering a unique device. Whether a new device is produced by an incumbent firm or a new entrant, that device has a relatively low probability of offering 4G service unless the incumbent (for incumbent devices) or the market (for entrant devices) is already producing 4G devices, in which case, this is more likely. This likely has to do with the time variation in availability of 4G service in the early part of the sample relative to the end of the sample. Finally, note TSR is not estimated since it is non-random and known.

Conclusion

I have developed a theoretical model of oligopolistic competition for the smartphone industry that expands on the existing applied dynamic oligopoly literature to include adaptive supply-side learning through the use of iterative BLP. I have then adapted existing methods of BBL to allow estimation of the structural parameters of the model. I have also developed iterative BLP to estimate the model in the presence of the supply-side learning mechanism in which firms learn about demand through time. The notable changes in learned demand over time as seen in Table 15 suggest that there can be substantial differences in estimated coefficients when using different data from different periods. Assuming that firms are no better demand modelers than BLP, incorporating adaptive learning into the firms' forecasts is important for modeling their value functions and expected future profits, which ultimately determine their strategic actions. Additionally, in using a two-step estimation routine such as BBL, the more accurate the estimates of the underlying value functions, the better will be our estimates of the structural parameters.

In applying these methods to the smartphone industry, I have shown that production with open source software (Android) is cheaper than proprietary software and also preferred by consumers, except to Apple products; I have also shown that there are substantial fixed costs associated with this market, both in terms of entering the market initially, as well as releasing new devices after entry. Interestingly, the scrap value for firms exiting the market are similar in magnitude to the entry costs which may be unsurprising given the large role of intellectual property in this market, intellectual property that often leads to litigation. (Chia [2012]) Indeed, this intellectual property may be sold when a firm exits the market, justifying the high scrap value.

TABLE 18. Transition Probabilities

	Price	Android	iOS	Windows	Other OS	3G	4G
Constant	329.2 ***	1.454 ***	-3.888 ***	-2.221 ***	-1.412 *	1.010 ***	-1.046 ***
	(26.31)	(0.3086)	(0.09149)	(0.2032)	(0.8419)	(0.1474)	(0.05983)
Vendor Median	21.30 ***	-0.5361 ***	0.4151 ***	-0.1737 ***	0.03020 ***	-0.1990 ***	0.1155 **
	(2.564)	(0.01839)	(0.05007)	(0.03638)	(0.005864)	(0.05601)	(0.05484)
Variance	24210 ***						
	(3314)						
Constant	426.9 ***	-1.585 ***	0.6932 ***	-10.78 ***	-0.06364 ***	0.6929 ***	-5.798 ***
	(58.69)	(0.1059)	(0.1450)	(0.6195)	(0.01837)	(0.09291)	(2.028)
Market Median	-77.57 *	1.919 ***	-14.89 ***	-11.92 ***	-1.036 ***	0.2938 ***	1.825 ***
	(44.46)	(0.2494)	(0.08786)	(1.630)	(0.09566)	(0.06632)	(0.7081)
Variance	23370 ***						
	(6162)						
Discrete	No	Yes	Yes	Yes	Yes	Yes	Yes

	16GB	64GB	Camera	Full Screen	Slider	Other Form
Constant	-1.617 *	-5.459 ***	5.853 ***	1.245 ***	-1.363 ***	-3.413 ***
	(0.9087)	(1.009)	(0.3294)	(0.4270)	(0.4997)	(0.6862)
Vendor Median	0.1182 ***	0.4918 ***	-0.4205 ***	-0.2994 ***	-0.1527 ***	0.01366 ***
	(0.01219)	(0.08246)	(0.03061)	(0.1040)	(0.01213)	(0.001453)
Variance						
Constant	-3.075 ***	-46.56 ***	10.66 ***	0.09361 ***	-0.8701 ***	-4.586 ***
	(0.4310)	(0.2086)	(3.780)	(0.01797)	(0.1820)	(0.3389)
Market Median	0.7694 ***	15.24 ***	11.80 ***	0.7956 ***	-0.6281 ***	0.2028 ***
	(0.1911)	(1.620)	(4.231)	(0.09917)	(0.1289)	(0.004714)
Variance						
Discrete	Yes	Yes	Yes	Yes	Yes	Yes

CHAPTER V

CONCLUSION

My dissertation research focuses on the telephony markets in the United States, with specific interest in the evolution of the industry from primarily landline driven to, in large part, cellular. The evolution of technology related to cell phones has been a major factor in the change and evolution of the market.

Early in the years of cell phones, the divestiture of AT&T's local landline services had recently changed the competitive landscape of the landline telephony market. At the time of this change, it was not yet clear whether cell phones would provide a complement or substitute to landline service, a question that would be of import to policy makers making regulatory decisions with respect to the landline market in the decades following the introduction of cell phones. Since cell phone technologies have developed, we have also seen the introduction of a new class of cell phone: the smartphone. Smartphone markets have not only changed the wireless telephone markets, but have evolved into one of the primary technology markets today. It is both the evolution from landline to cell phone, and the evolution of smartphones and dynamic strategic competition on which I focus my research.

The substantive work of my dissertation begins with a chapter on the evolution of consumer choices in the landline and cell phone telephony market. Implementing discrete choice econometric techniques, I find that different market segments are responsible for the adoption of cell phones through time; specifically, it is younger and larger households that drive adoption of the new technology, with larger households often maintaining both telephony services in the household. With these results in hand, I develop and apply a decomposition of a measure of substitutability and find that the substitutability of landlines and cell phones has changed significantly over the sample period from 1994 to

2012. These two technologies have become more substitutable through time, indicating an increasing competitive constraint on landlines from cell phones.

In studying this problem, I searched for a flexible alternative to modeling the evolution of choice through time. In reading a paper by Engle [2014], I was introduced to the concept of time-varying parameters. In the context of discrete choice, changes in parameters may reflect changes in preferences and culture, but most prominently in this case is the change in technology. If the utility function of the discrete choice model reflects the value of the underlying alternatives to consumers, and the underlying alternatives change in a meaningful way, then, indeed, the utility function should also change. To model this, I develop an econometric methodology capable of estimating latent-dependent variable models, such as discrete choice logit models, with time-varying parameters. I then apply this to the US telephone industry. This methodology allows the decoupling of price sensitivity from the increase in value from evolving technologies. The results suggest that, while cell phones have gotten better with time, consumers have also become more price sensitive. This, again, points to increasing competition for landline service providers from cell phones due to the increased substitutability of these products.

In the final substantive chapter of my dissertation, I model the US smartphone industry in a dynamic setting. I extend the model of Ericson and Pakes [1995a] to allow for adaptive learning and apply this model to the data using an iterative version of Berry et al. [1995] and the empirical estimation routine of Bajari et al. [2007]. In doing so, I find evidence of substantial fixed costs associated with entering the industry and releasing new devices reflecting the presence of economically important intellectual property in this market. The results also suggest that the demand parameters that are learned by the firms through the employment of econometricians may, indeed, change through time, which would cause errors in the computation of value functions if not properly addressed. With these results, I can value various product attributes to consumers and their production costs to firms.

The work of the dissertation research made use of various tools from my economic toolkit in order to study the US telephony industry, from utility maximization and consumer choice, to dynamic oligopoly models of imperfect competition in the presence of differentiated products. This also involved substantial econometrics including maximum likelihood, Bayesian MCMC techniques with a SMC filter, generalized method of moments, and a minimum distance estimator, among others. Ultimately, I have developed a research program that covers the vast majority of evolution in cell phone technologies, as well as the industrial economics that have led to important change in the industry for incumbent firms, potential entrants, policy-makers, and the US consumer.

APPENDIX A

HOUSEHOLD CHOICE

As discussed in Section 2.3, the telephony service alternatives for households are (1) no phone, (2) just landline, (3) just cell phone, or (4) both. The data contain expenditures for a household from the quarter prior to the interview in many different categories defined by a universal classification code (UCC).[1] There is a unique UCC for cell phone expenditures and another unique UCC for landline expenditures. For a household with strictly-positive expenditure on the UCC of landline or cell service,[2] I record this expenditure as a choice between alternatives. That is, for an expenditure greater than zero, the household is recorded as choosing that category but recorded as not choosing that category otherwise. Choosing no phone is defined as zero expenditure in both categories while choosing both is defined as positive expenditure in both categories. The data are available dating to before the introduction of cell phone services, but all records of cell phone expenses are zero-valued in this dataset prior to 1994 even though cell phones were available about a decade earlier. For this reason, the usable data range from 1994 to 2012, a 19-year period during which the data contain more than 296,000 household choices between the defined alternatives.

[1]I also supplement the interview data with diary data for CUs that do not have expenditures in the interview data. In this case, I use variables TELRESD, UTLPROPI coded 96, and TELCELL for appropriate years.

[2]The UCC for landline service is 270101 while the UCC for cell service is 270102

APPENDIX B

CONSTRUCTED PRICE VARIABLES

In this section, I present two approaches to constructing prices from the expenditure data. The main goal of these approaches is to construct a measure of the price of a single phone. The first approach assumes all family sizes face the same prices. The second approach allows for different family sizes to face different prices with the idea being that families can get "family plans", which offer discounts on multiple lines.

The first approach is to calculate the median expenditure by UCC for both cell and landline among CUs with family size equal to one who have nonzero expenditure in that category in a given year. This estimate assumes that CUs with family size of one only purchase one landline or one cell phone service given they choose that option. This is a reasonable assumption given that most individuals living alone do not have any reason to purchase more than one of each service and the median will certainly avoid any outliers.

The second approach allows for a different price for each option, family-size, region, year tuple. This approach is as follows:

1. Take the median expenditure on an option by single-person households with positive expenditure in a category. Define this as the base price for the category, region, year triple and do this for each of these triples.
2. For each family with family size greater than 1 and positive expenditure in a given category, divide the expenditure by one and calculate the absolute difference between this and the base price from step 1.
3. Repeat step 2 for each integer from 1 through the family size. That is, first divide the expenditure by one, then divide it by two, and so forth.
4. From these multiple prices (there are the same number of possible prices as there are individuals in the family), select the one with the smallest absolute difference between it and the base price for the option, region, year triple and call this the "temporary price".

5. For each observed family size, define the price for the option as the median of this "temporary price" among households of that family size with positive expenditure in that category. Again, this step is done once for each option, region, year triple.
6. For some family sizes, there are no observations for an option. In this case, set the price equal to the price for the next family size down.

In either case, the time-series obtained through this process is less than ideal, likely due to changes in cell phone capabilies that require more extensive service plans indicating higher prices even though comparable service plans are generally decreasing in price through time. Nonetheless, my price proxies are highly correlated with the CPI categories for landline and cell phone prices, with correlation coefficients of 0.8681 and 0.7746, respectively.

APPENDIX C

COMPUTATIONAL NOTES

The high quantity of simulation involved in the estimation strategy presents a large computational burden. Specifically, for each draw of the MH algorithm, there are 10,000 particles drawn for each period, and for each of those period-particle pairs, the likelihood of that period's data must be computed for the parameters drawn. Worse still is that these likelihood computations involve exponents and logarithms that are relatively costly to compute. To provide some idea to substantiate the computational burden, the likelihood of a single observation for a single period is given by:

$$p(Y_t|\beta_t^d) = \frac{exp(X_{it}\beta_{ijt}^X + Z_{jt}\beta_{it}^Z)}{\sum_{m=1}^{J} exp(X_{it}\beta_{imt}^X + Z_{mt}\beta_{it}^Z)}.$$

This is then computed once for each particle for each observation in a given period, and for each period. With about 15.5 thousand observations per period, 19 periods, and 10,000 particles, this involves computation of the above single-decision likelihood function about 3 billion times per MH draw. If I am concerned about Monte Carlo error and re-evaluate the likelihood of the previous draw of MH, the total number of evaluations for estimation doubles. Additionally, working in log-likelihoods, which is essential so the probabilities do not get rounded to zero, also requires taking the log of each of these as well.

After computing the likelihood of each particle for a given period, the particles must then be redrawn using the likelihood of each particle as a relative weight. The main MH algorithm and much of the filter is programmed in Matlab. The computation of particle likelihoods was initially coded in a Matlab MEX file with C++ to maximize speed and is now in CUDA/C, but this level of simulation takes significant amounts of time. Using the University of Oregon's Applied Computational Instrument for Scientific Synthesis (ACISS) with 72GB RAM, and 12 processor cores or an NVIDIA M2070 GPU computing likelihoods in parallel, the 81,000 MH draws, even with this relatively limited model, took approximately four weeks on the parallel CPUs or as little as 6 days on the GPU. I have since used the efficiency of the GPU to increase the number of MH draws to 500,000 which has improved the precision of the posteriors significantly as the adaptive proposal has become more efficient.

APPENDIX D

ADDITIONAL TABLES

TABLE 19. Posterior Distributions for θ

ALT.	VARIABLE	PARAMETER	5th-tile	25th-tile	Median	75th-tile	95th-tile	StdDev
	Price	β_{1993}	-3.87	-2.92	-2.25	-1.66	-1.13	0.63
		σ_ω	5.35	6.99	12.90	20.23	31.58	6.62
		τ	-1.38	-0.42	0.41	1.38	3.46	0.90
Cell	Constant	β_{1993}	-68.30	-59.20	-49.54	-39.04	-25.35	10.08
		σ_ω	137.45	165.43	195.53	230.95	287.94	32.76
		τ	-15.70	3.11	17.26	25.74	35.05	11.31
Cell	Age	β_{1993}	-40.94	-36.11	-31.22	-25.99	-20.06	5.06
		σ_ω	7.02	8.26	9.88	12.14	14.48	1.94
		τ	0.61	1.57	2.60	3.58	4.82	1.01
Cell	Family Size	β_{1993}	-37.21	-29.12	-19.96	-7.21	2.81	10.96
		σ_ω	53.98	69.59	90.04	130.84	195.65	30.63
		τ	2.06	5.41	9.12	12.84	18.19	3.71
Both	Constant	β_{1993}	-56.77	-47.81	-35.35	-21.24	-6.84	13.28
		σ_ω	54.60	62.41	68.56	77.09	85.04	7.34
		τ	35.03	42.50	53.15	71.67	79.50	14.58
Both	Age	β_{1993}	-6.43	-5.10	-3.84	-2.24	-0.66	1.43
		σ_ω	1.17	1.43	1.71	2.02	2.40	0.30
		τ	-0.37	-0.24	-0.11	0.02	0.11	0.13
Both	Family Size	β_{1993}	-26.12	-12.71	-1.67	11.56	20.65	12.13
		σ_ω	31.94	40.00	48.59	59.03	71.87	9.52

τ	-30.35	-23.68	-15.96	-10.64	-4.96	6.52

TABLE 20. Posterior Distributions for β_t

ALT.	VARIABLE	Year	5th-tile	25th-tile	Median	75th-tile	95th-tile	StdDev
	Price	1994	-3.87	-2.92	-2.25	-1.66	-1.13	0.63
		1995	-5.35	-4.33	-3.43	-2.62	-1.90	0.86
		1996	-6.97	-5.82	-4.65	-3.61	-2.70	1.11
		1997	-9.76	-8.11	-6.44	-5.10	-3.95	1.50
		1998	-12.14	-9.88	-7.99	-6.33	-4.91	1.78
		1999	-13.87	-11.24	-9.07	-7.24	-5.63	2.00
		2000	-14.09	-11.38	-9.17	-7.39	-5.76	1.99
		2001	-14.67	-11.71	-9.46	-7.53	-5.88	2.09
		2002	-15.91	-12.75	-10.24	-8.14	-6.29	2.31
		2003	-17.11	-13.69	-10.96	-8.74	-6.77	2.47
		2004	-17.50	-13.93	-11.10	-8.83	-6.76	2.55
		2005	-17.95	-14.31	-11.43	-9.06	-6.93	2.63
		2006	-19.72	-15.83	-12.70	-10.14	-7.70	2.85
		2007	-20.48	-16.42	-13.06	-10.40	-7.84	3.01
		2008	-21.46	-17.10	-13.73	-10.79	-8.17	3.16
		2009	-22.42	-17.93	-14.19	-11.18	-8.47	3.37
		2010	-22.82	-18.12	-14.40	-11.21	-8.48	3.45
		2011	-24.20	-19.13	-15.16	-11.83	-8.89	3.65
		2012	-26.84	-21.15	-16.60	-12.93	-9.47	4.11
Cell	Constant	1994	-147.07	-90.63	-51.05	-11.73	31.61	39.45
		1995	-197.60	-115.69	-53.97	-3.71	51.15	55.99

		1996	-183.40	-92.52	-23.99	30.08	91.74	61.30
		1997	-255.27	-137.29	-46.31	21.97	88.42	79.63
		1998	-240.00	-121.23	-29.70	42.02	112.64	81.63
		1999	-163.50	-65.72	10.16	75.20	142.86	70.46
		2000	-134.29	-40.74	34.45	97.78	165.25	69.26
		2001	-108.16	-13.89	59.94	123.64	190.28	68.77
		2002	-49.79	28.17	92.51	148.25	207.21	60.04
		2003	93.29	143.02	186.32	230.89	283.40	43.94
		2004	143.61	189.06	231.78	276.11	327.85	43.52
		2005	187.97	231.80	274.01	316.66	367.75	42.43
		2006	203.26	245.85	285.72	328.64	376.85	41.40
		2007	222.35	265.83	307.98	350.88	397.66	42.53
		2008	261.28	308.56	354.40	401.51	452.69	46.47
		2009	269.72	318.62	368.82	420.68	474.62	51.03
		2010	299.25	355.11	409.33	464.13	526.04	54.51
		2011	308.08	365.63	424.88	481.22	545.14	57.79
		2012	309.64	369.27	424.68	480.66	539.00	55.69
Cell	Age	1994	-41.29	-34.74	-29.26	-23.90	-17.57	5.42
		1995	-40.45	-33.53	-27.52	-21.77	-15.78	5.88
		1996	-32.55	-25.97	-20.35	-15.16	-10.35	5.40
		1997	-33.90	-27.05	-21.33	-16.14	-11.11	5.45
		1998	-27.82	-21.34	-15.91	-11.08	-6.90	5.13
		1999	-16.37	-11.34	-7.60	-4.50	-2.05	3.42
		2000	-11.67	-7.98	-5.25	-3.04	-1.09	2.47
		2001	-8.47	-5.57	-3.45	-1.60	-0.02	1.99
		2002	-7.47	-5.05	-3.27	-1.82	-0.48	1.62

		2003	-6.11	-4.47	-3.19	-2.10	-1.10	1.19
		2004	-5.26	-3.96	-2.92	-2.03	-1.19	0.96
		2005	-4.81	-3.70	-2.82	-2.03	-1.27	0.84
		2006	-5.32	-4.26	-3.40	-2.60	-1.84	0.83
		2007	-4.28	-3.44	-2.75	-2.10	-1.48	0.67
		2008	-4.48	-3.61	-2.89	-2.24	-1.61	0.68
		2009	-3.77	-3.03	-2.40	-1.81	-1.24	0.61
		2010	-3.63	-2.95	-2.33	-1.75	-1.17	0.60
		2011	-3.73	-3.01	-2.40	-1.82	-1.28	0.59
		2012	-4.09	-3.36	-2.75	-2.16	-1.58	0.60
Cell	Family Size	1994	-75.27	-47.04	-24.40	-1.60	22.25	22.72
		1995	-108.38	-66.03	-37.51	-11.28	13.07	27.38
		1996	-53.83	-26.51	-2.48	19.27	41.70	22.89
		1997	-103.52	-61.11	-31.16	-4.62	20.04	28.24
		1998	-131.08	-79.61	-44.21	-16.00	11.41	31.81
		1999	-95.79	-60.60	-33.87	-12.85	6.47	23.87
		2000	-120.13	-79.05	-49.25	-25.64	-4.71	26.70
		2001	-142.93	-97.48	-63.09	-35.94	-13.69	30.77
		2002	-71.98	-46.79	-27.80	-10.85	4.38	17.97
		2003	-62.05	-42.80	-27.67	-14.54	-2.68	14.13
		2004	-56.13	-39.60	-26.88	-15.94	-5.49	11.83
		2005	-39.39	-28.07	-18.52	-9.57	-1.04	9.25
		2006	-32.40	-22.50	-14.44	-7.19	-0.03	7.65
		2007	-26.32	-18.14	-10.70	-4.01	2.94	7.07
		2008	-29.85	-21.20	-13.79	-6.95	-0.21	7.12
		2009	-25.03	-17.43	-10.79	-4.69	1.45	6.37

		2010	-20.17	-13.02	-6.67	-0.71	5.70	6.16
		2011	-18.28	-11.61	-5.48	0.33	6.89	5.97
		2012	-22.77	-15.82	-9.66	-3.39	3.29	6.21
Both	Constant	1994	38.12	58.89	82.09	103.88	124.77	22.49
		1995	81.58	111.13	143.27	177.27	209.80	33.07
		1996	114.64	150.98	193.02	239.97	288.56	44.50
		1997	140.74	181.90	229.69	287.63	350.22	52.87
		1998	165.73	213.48	268.13	332.40	408.07	59.46
		1999	193.12	247.34	308.43	383.13	473.98	67.90
		2000	223.99	286.95	357.48	444.28	550.93	78.67
		2001	255.27	324.64	406.50	503.77	629.47	89.56
		2002	282.82	361.04	450.06	558.53	697.60	98.74
		2003	308.34	394.17	493.33	613.48	769.59	109.65
		2004	338.81	434.22	539.88	671.45	841.25	118.62
		2005	370.79	472.83	585.49	734.25	910.63	130.71
		2006	397.21	505.81	626.99	785.23	974.10	139.71
		2007	424.44	544.71	675.78	845.65	1047.60	150.47
		2008	456.07	581.62	722.41	897.06	1113.74	157.72
		2009	483.79	621.24	770.44	952.30	1182.93	165.53
		2010	516.17	661.06	816.50	1011.37	1256.32	175.16
		2011	548.50	699.84	859.96	1063.04	1322.65	181.60
		2012	574.55	731.57	900.57	1112.78	1385.08	190.61
Both	Age	1994	-3.33	-1.92	-0.85	-0.26	0.12	0.83
		1995	-0.73	-0.40	-0.21	-0.08	0.07	0.16
		1996	-0.45	-0.27	-0.15	-0.04	0.06	0.11
		1997	-0.29	-0.18	-0.09	-0.02	0.06	0.08

		1998	-0.25	-0.16	-0.08	0.00	0.07	0.08
		1999	-0.34	-0.21	-0.10	0.00	0.11	0.11
		2000	-0.30	-0.18	-0.08	0.02	0.13	0.10
		2001	-0.29	-0.18	-0.08	0.02	0.12	0.10
		2002	-0.43	-0.29	-0.16	-0.03	0.10	0.13
		2003	-0.52	-0.33	-0.15	0.01	0.19	0.17
		2004	-0.68	-0.46	-0.27	-0.09	0.10	0.18
		2005	-0.78	-0.53	-0.30	-0.09	0.13	0.22
		2006	-0.86	-0.59	-0.35	-0.11	0.14	0.24
		2007	-0.97	-0.66	-0.38	-0.12	0.15	0.27
		2008	-1.08	-0.75	-0.46	-0.18	0.11	0.28
		2009	-1.25	-0.87	-0.52	-0.19	0.15	0.34
		2010	-1.37	-0.92	-0.55	-0.17	0.21	0.37
		2011	-1.56	-1.09	-0.68	-0.27	0.16	0.41
		2012	-1.89	-1.36	-0.90	-0.46	0.02	0.45
Both	Family Size	1994	-3.12	0.42	3.57	7.99	14.24	3.79
		1995	-1.69	-0.28	0.86	2.14	3.75	1.21
		1996	-2.50	-1.17	-0.04	1.03	2.16	1.10
		1997	-1.28	-0.35	0.47	1.29	2.23	0.82
		1998	-1.33	-0.44	0.38	1.21	2.13	0.83
		1999	-2.02	-0.61	0.64	1.85	3.22	1.23
		2000	-1.51	-0.30	0.80	2.00	3.25	1.15
		2001	-1.85	-0.59	0.61	1.74	3.02	1.16
		2002	-1.81	-0.23	1.36	2.86	4.59	1.55
		2003	-2.68	-0.45	1.54	3.48	5.76	1.97
		2004	-3.11	-0.75	1.52	3.85	6.45	2.30

2005	-4.13	-1.25	1.53	4.20	7.42	2.73
2006	-2.50	0.39	3.28	6.39	9.71	3.00
2007	-2.66	1.12	4.87	8.63	12.85	3.75
2008	-3.25	0.33	3.64	7.14	11.25	3.40
2009	-4.96	-0.65	3.21	7.42	12.27	4.04
2010	-5.69	-0.82	3.55	8.29	13.54	4.56
2011	-9.04	-3.83	1.16	6.36	12.20	5.10
2012	-9.97	-4.25	1.19	6.69	12.67	5.47

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