Essays on Estimating Network Effects and Switching Costs

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Eidesstattliche Erklärung

Hiermit erkläre ich, dass ich die vorliegende Dissertation selbstständig angefertigt und die benutzten Hilfsmittel vollständig und deutlich angegeben habe.

Mannheim, 2. Juni 2015 Stefan Weiergräber

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1 General Introduction

This thesis consists of three single-authored essays that address open research questions in the empirical analysis of network industries. Empirically analyzing these markets is extremely difficult. Because of several industry particularities standard economic and econometric models can generally not be applied to examine network industries. Switching costs and network effects are two prominent examples of these market characteristics.

A *switching cost* is a one-time utility loss that consumers incur when buying a different product today than in the previous period. This creates an incentive for consumers to continue to buy from the same firm over time. Throughout this thesis the term *network effect* denotes a direct firm-specific network effect, i.e. the utility from using a particular product increases in the number of other consumers who use the same product. This creates an incentive for consumers to coordinate and conform with the crowd.

In isolation, switching costs and network effects have been analyzed extensively, both theoretically and empirically, cf. Farrell and Klemperer (2007). However, in most network industries, switching costs and network effects occur simultaneously and interact.

Regulators around the world are often concerned with network industries. In most cases, demand exhibits massive consumer inertia providing empirical evidence that it is easy for incumbent firms to defend their dominating position and potentially exploit locked-in consumers. A prime example for such an industry is the wireless industry. In order to design effective policies, it is important to know where the inertia comes from because policy implications may be very different depending on the sources of the inertia.

Empirically disentangling these sources is a very challenging task. Switching costs link consumers' decisions across periods and therefore call for modeling demand using a dynamic model. In terms of both identification and estimation, these models are much more involved than static frameworks. The identification of network effects is extremely intricate, mostly because of the *reflection problem* (Manski 1993). The reflection problem comes from the fact that a network effect tries to explain the market structure, i.e. the distribution of market shares, by market shares leading to severe econometric identification problems.

In Chapter 2 and 3, I present structural demand models which allow to disentangle different sources of consumer inertia based only on group-level data. The availability of group-level data allows me to observe market shares and churn rates disaggregated by different demographic consumer types and local markets. This type of data is usually much easier to acquire on a large scale than individual-level data. One of the main contributions of this thesis is to show that group-level data is powerful enough to separate the effects of switching costs and network effects from preference heterogeneity. Although my models are tailored towards the US wireless industry, they are applicable to a broad range of network industries.

Chapter 2 presents the basic empirical framework to estimate demand. In contrast to Chapter 3, consumers are myopic, i.e. their previous choice affects current behavior, but individuals are not forward-looking. The use of group-level data allows me to identify preference heterogeneity from consumer type-specific market shares and switching costs from churn rates. Identification of a localized network effect comes from comparing the dynamics of distinct local markets. The central condition for identification is that neither the characteristics defining consumer heterogeneity nor the characteristics defining reference groups are a (weak) subset of the other. Applying my framework to the US wireless industry, I find that both switching costs and network effects play an important role: Estimates of switching costs range from US-$ 316 to US-$ 630. The willingness to pay for a 20 percentage point increase in an operator's market share is on average US-$ 22 per month. Counterfactual simulations illustrate that both effects are important determinants of consumers' price elasticities potentially translating into market power that helps large carriers in defending their dominant position.

Chapter 3 extends the framework proposed in Chapter 2 by allowing consumers to be forward-looking when buying a product. In most high-tech consumer goods industries, it is much more realistic to assume that consumers are forward-looking rather than myopic. I discuss the additional assumptions for identification of the network effect in a dynamic model and estimate it using group-level data on the US wireless industry. Ex-ante, it is not clear how the estimates would change when going from a myopic to a dynamic model. Qualitatively, the results from the dynamic model are in line with the ones from Chapter 2. Both switching costs and network effects are significant. In comparison to the myopic model, estimates of switching costs and network effects are on average 30% to 50% lower. When analyzing the demand effects of perfect network compatibility or a reduction in switching costs, forward-looking consumers react less strongly but much faster than in the myopic model.

Switching costs and network effects do not only have significant effects on demand. They also affect firms' pricing strategies because an installed customer base is a valuable asset. Consequently, supply side behavior should be inherently dynamic, independently of whether consumers are myopic or forward-looking. Therefore, static models are inappropriate to analyze firm behavior and to estimate marginal costs.

Chapter 4 addresses this issue. I outline an empirical model of dynamic platform competition. When setting prices, firms face a trade-off between a *harvest* and an *investment* motive. On the one hand, setting high prices will increase current profits by harvesting locked-in consumers. On the other hand, lowering prices can be profitable as it draws in consumers today. Due to the network effect, additional consumers will be attracted to the firm leading to a larger installed base which can be harvested in the future. Recent theoretical research shows that this non-trivial trade-off has important implications for the industry dynamics. I outline how marginal costs can be estimated when firms optimize dynamically. The estimation algorithm combines two-step estimation and forward-simulation techniques. The implementation is computationally very intensive and therefore left for future research. When combined with the demand models in Chapter 2 or Chapter 3, the supply side model allows for rich counterfactuals. For example, one can assess how firms' pricing strategies change, when switching costs or network effects are regulated. Moreover, the model could shed light on the effects of mergers in network industries which is a regularly and heavily debated topic.

2 Disentangling Sources of Consumer Inertia - Network Effects and Switching Costs in the US Wireless Industry

2.1 Introduction

In many high-tech consumer goods industries purchase decisions are characterized by the presence of both switching costs and network effects. The individual importance of both effects has been studied extensively, cf. Farrell and Klemperer (2007). While switching costs create consumer lock-in via a consumer's own previous choice, network effects make a consumer prefer a product that many other consumers already use. Although not necessarily the case, this often leads to inefficient outcomes and substantially alters the nature of competition generally favoring large incumbent firms.

The interaction between switching costs and network effects is much less studied. However, it is exactly this interplay that can be particularly problematic. In fast-changing industries like the wireless service industry, consumers are usually not able to forecast the technology evolution well over a longer horizon. When switching costs impede consumers from re-optimizing quickly, network effects and switching costs may amplify each other giving large firms not only extensive but also very persistent market power. In these types of industries, the typical concentrated market structure with only few firms and heavy consumer inertia constantly raises regulators' concern. In order to design effective policies, it is crucial to know where consumer inertia comes from. For example, policies reducing switching costs, such as number portability in the wireless industry, may not have a big effect on customer mobility if inertia is mostly due to network effects.

By only looking at the aggregate industry structure, it is usually hard to empirically disentangle whether consumers stick with a dominant firm because of preference heterogeneity, switching costs or network effects. In this context, the identification of network effects is particularly problematic, especially when only aggregate data are available. These problems are very similar to Manski (1993)'s reflection problem: the fact that market shares occur on both sides of an regression equation requires additional model structure and more sophisticated identification arguments compared to analyzing demand dynamics in non-network industries. These difficulties have led most of the literature to make restrictive assumptions or to ignore one of the effects in order to quantify the others. Restricted models are likely to result in confounded estimates and wrong conclusions for economic policy, however.

To tackle these problems, I develop an empirical framework that allows me to separately identify preference heterogeneity from direct network effects and state-dependence due to switching costs. Throughout this thesis, the term *network effect* denotes a direct, anonymous, firm-specific network effect. It measures the effect of a product's aggregate market share within a consumer's reference group, i.e. the group of individuals a consumer cares about, on this consumer's flow utility from using that product. I model heterogeneous consumers in a discrete-choice framework with decisions being driven by products' observed and unobserved quality characteristics, an individual consumer's choice in the previous period as well as the contemporaneous average behavior of her reference group.

In the identification section, I demonstrate under which assumptions the reflection problem can be transformed into a well-studied endogeneity problem and how switching costs and certain kinds of network effects - especially those that are similar to a local spillover - can be separately identified from preference heterogeneity. I argue that the reflection problem and the associated endogeneity problem can be overcome as long as neither the determinants of consumer heterogeneity nor the determinants of the reference group are a weak subset of the other. The implications of this condition are twofold. First, it enables me to observe individuals with identical preferences in different network environments yielding the necessary variation in the data. Second, demand shifters that affect different consumer types within a reference group differently can serve as exclusion restrictions and the basis for instruments for a product's market share.

I estimate the model analyzing demand for wireless services in the US focusing on geographically localized network effects. For the estimation, I use a panel of group-specific market shares constructed from a large-scale survey. The detailed group-level data contain market shares disaggregated by different demographic types and different local markets which allows me to identify consumers' preference heterogeneity from type-specific market shares. Aggregate churn rates, i.e. the fraction of consumers who cancel their contract within a period, identify the switching cost parameters. In my model, the switching cost measures a one-time utility loss associated with the switching process. Differences in the evolution of separated local markets identify a localized network effect. As long as consumers' preference heterogeneity does not systematically differ across local markets and time and consumers' reference groups consists of at least 2 different types, the model can be estimated using an extension of the classical framework by Berry, Levinsohn, Pakes (1995, henceforth BLP).

My estimates of both switching costs and network effects are large and significant. Switching costs vary across consumer types from US-$ 316 to US-$ 630 revealing substantial heterogeneity. The willingness to pay for a 20%-point increase in an operator's market share within a consumer's reference group is around US-$ 22 per month varying across consumer types from US-$ 18 to US-$ 25. Estimating the model ignoring either switching costs or network effects results in implausibly large estimates of the other effect and a substantially worse model fit. In counterfactual simulations, I demonstrate that network effects and switching costs are important determinants of consumers' price elasticities. Implementing perfect network compatibility results in lower own-price elasticities and much more homogeneous cross-price elasticities. Not surprisingly, decreasing switching costs results in significantly larger price elasticities. Short-run elasticities almost triple and the difference between medium-run and long-run elasticities diminishes. In both simulations, the smaller operators (Sprint and T-Mobile) would gain substantial market share with T-Mobile generally profiting most.

This paper is related to several strands of literature. There is a wide range of studies on switching cost and network effects in the wireless industry most of which follow a static and reduced-form approach. Moreover, almost all studies focus only on either switching costs or network effects, but not both simultaneously. In contrast to the reduced-form studies, for example by Kim and Kwon (2003) and Kim, Park, and Jeong (2004), I follow a structural approach that allows me to conduct counterfactual analysis and explicitly take the dynamic nature of subscription decisions into account.

Grajek (2010) estimates product-specific network effects and compatibility in the Polish wireless market. While he follows a structural approach his model is restrictive as he does not allow consumers to switch operators. Cullen and Shcherbakov (2010) estimate a structural demand model for bundles of handsets and service provider, but abstract from consumer heterogeneity and the presence of network effects. Yang (2011) is to the best of my knowledge the only study that considers direct network effects and switching costs simultaneously in a dynamic model. However, he does not take into account consumer heterogeneity and the reflection problem is not dealt with.

In contrast, I provide identification arguments for a structural demand model with consumer heterogeneity, switching costs and direct network effects exploiting detailed group-level data. My model allows me to estimate network effects within an extension of the methodology by Berry, Levinsohn, and Pakes (1995) complemented with dynamic panel techniques and elements from the dynamic demand literature. Shcherbakov (2013) and Nosal (2012) use a dynamic demand framework to quantify consumer switching costs in non-network industries (cable TV and health plan choice). The structural identification of network effects shares some features with the sorting problems dealt with in the housing market literature. For example Bayer and Timmins (2007) quantify local spillovers in a static model of location choice. Identification issues in their model arise because all variation in choices can be explained by a vector of location fixed effects. Similar to my method, they apply an instrumental variable approach in the style of BLP to decompose the location-fixed effects into spillovers and unobserved quality characteristics. Lee (2013) quantifies indirect network effects in the video game industry. For estimating direct network effects, I rely on similar moment conditions as his paper.

The remainder of this paper is structured as follows: The next section describes important characteristics of the US wireless industry. Section 2.3 presents the economic model. Section 2.4 describes the data used for the estimation. Section 2.5 develops the identification arguments and outlines the estimation strategy. Estimation results and counterfactual experiments are presented in Sections 2.6 and 2.7. Section 2.8 concludes.

2.2 Industry characteristics

During my sample period (2006-2010), the US wireless industry was a prime example of an industry in which switching costs and network effects interact. Two large mergers in 2004 (AT&T and Cingular) and 2005 (Sprint and Nextel) led to an oligopolistic market structure with 4 dominant players and constant scrutiny by the FCC. The two biggest operators (AT&T and Verizon) still have a joint market share of almost 70 %, while each of the two smaller operators (Sprint and T-Mobile) controls 10-15 % of the market. The remaining market is shared by several smaller operators often with limited regional coverage mostly in rural areas. While the smaller operators usually sell more specialized products, the four major carriers offer only slightly differentiated service bundles with respect to contract types, payment schemes, tariff structure, handsets subsidized and customer service. However, carriers can differ significantly in local coverage quality.[1]

Operator market shares vary significantly across local markets, but are very persistent over time. In addition, my micro data indicate that the vast majority of cellphone users has not switched their provider for more than 3 years. The FCC has been concerned about this consumer inertia and attributed it to the presence of switching costs. Policy measures, such as number portability in 2003, have been undertaken to reduce switching costs. However, customer mobility across operators remains low with average monthly churn rates mostly below 1-2 %. In addition, large carriers generally have substantially lower churn rates than smaller ones. Switching costs in the wireless industry can be explicit, for example in the form of early-termination-fees or implicit through hassle costs that consumers incur when switching their operator. During my sample period all post-paid contracts specified an early-termination-fee of up to US-$ 350 that a consumer had to pay to end her contract prematurely. Implicit hassle costs constitute an additional component of switching costs because consumers in general have to find out how to cancel a contract and incur opportunity costs of time, for example for filling out the necessary paper work.

Network effects in modern wireless communications services are largely *tariff-mediated*, i.e. generated by the predominant contract structures. Postpaid contracts in the US typically take the form of 24-months contracts specifying a monthly fee

[1] For a detailed description of variation in local coverage quality see the discussion in Sinkinson (2011).

plus some included number of *anytime minutes* that can be used to make calls at any time to any network (for example a 400-anytime-minute package for 40 US-$ per month). During my sample period, most of these contracts included unlimited *night and weekend minutes* as well as free calls to an operator's own network.[2] My data reveals that at the beginning of my sample period (January 2006) the majority of consumers (more than 75%) had plans with free on-net calls. This number decreased continuously to slightly above 50% at the end of my sample period (December 2010). Afterwards, network effects in the form of on-net call discounts have continued to decline as wireless carriers shifted their business models from selling phone services to data plans bundled with unlimited anytime-minutes. Given the historical contract structures and the fact that many consumers stick to their old contracts for years, on-net discounts should still have played a substantial role during my sample period.

The mere presence of on-net discounts however need not generate network effects as operators could adjust their prices in such a way that small operators compensate for their smaller network by lower prices. Interestingly, several papers found that even after controlling for price differentials, consumers perceive networks as incompatible, i.e. they seem to appreciate being on a larger network per se (Grajek 2010; Kim and Kwon 2003; Birke and Swann 2006). This may be due to several reasons. First, it is not clear, that operators really charge fully off-setting prices. Second, there can be more subtle contract features from which consumers benefit more easily if they are on the same network. For example, under a *receiving-party-pays* regime[3] as in the US, consumers can have an incentive to coordinate on symmetric contract features, for example on identical relative prices for voice minutes and text messages as this facilitates coordinating on a preferred mode of communication. These features are usually slightly different across operators but are identical across contracts within an operator. In addition, consumers may appreciate a large network as an insurance against having to buy more expensive off-net minutes in case of unanticipated calls. Finally, they may simply derive psychological utility from conforming with their peers (Grajek 2010).

[2]For an overview of typical contract features during my sample period see Section 2.5 in the Appendix.

[3]While in a *receiving-party-pays* regime both, the caller and the receiver, are charged for airtime, under a *calling-party-pays* regime, only the caller is charged for making a call.

2.3 Model

In this section, I present a structural discrete-choice model in which consumer decisions are driven by both switching costs and network effects. The framework extends the literature on estimating demand models with state-dependence by incorporating direct network effects. Although in general applicable to a broad range of network industries, I tailor the model towards the US wireless industry.

Each period, consumers can choose a wireless network to subscribe to. There are 4 major operators and a fringe of smaller operators which constitute the outside option. This yields a choice set with 5 different products in total. Modeling the technology adoption decision as in Grajek and Kretschmer (2009) or Goolsbee and Klenow (2002) is conceptually straightforward and can be done by splitting up the choice *not subscribing to the major 4* into *subscribing to a small operator* and *no wireless service at all.* Given that the wireless penetration rate was already very high (over 90%) during my sample period, I abstract from the adoption decision and assume that every consumer is subscribed to a wireless carrier. In contrast to Cullen and Shcherbakov (2010), I abstract from consumers' specific handset choice. In addition, I do not model the decision of which specific plan to choose. Each consumer is assigned to a local market based on his residency. I classify geographic markets similarly to Nielsen's DMA-definition. A DMA (designated market area) is defined as a collection of counties of similar magnitude as a metropolitan statistical area. The time period of observation is a quarter.

Consumers have heterogeneous preferences as a function of their individual demographic characteristics d. This results in a discrete number of consumer types which may for example be defined by age and income. The flow utility of consumer i belonging to demographic group d in geographic market m from being subscribed to operator j in quarter t is given by a multiplicative function in usage quantity q^d_{jmt} and quality. I treat usage quantity as fixed and exogenously given. Quality is modeled as a linear function in observable product characteristics (X) and unobserved demand shocks (ξ). Due to the presence of network effects, a large network size ($s^{r_d}_j$) increases consumers' utility of being subscribed to operator j. Here, r_d indexes a consumer's reference group which need not be equal to her type d, i.e. consumers are allowed to also care about other types than their own. I assume that consumes are myopic so that they do not form explicit beliefs about the future evolution of the industry. However, the model has a dynamic component as consumers incur a switching cost (ψ) when choosing a different provider today than in the previous period. The per-period utility function is specified as follows:

$$u^i_{jmt} = \underbrace{(X^d_{jmt}\beta^d + \gamma^d p^d_{jt} + \xi^d_{jmt} + \alpha^d s^{r_d}_{jmt})q^d_{jmt}}_{\delta^d_{jmt}} + \psi^d \mathbb{1}_{\{a_{it-1} \neq a_{it}\}} + \epsilon^i_{jmt}$$

where X^d_{jmt} contains operator-fixed effects and observed product quality characteristics varying by local market m and consumer type d, p_{jt} denotes the average price per unit of phone service of operator j in period t. The structural parameters (β,γ, α, ψ, ξ) differ across demographic types, but are constant within a group d. In order to reduce the number of parameters to be estimated, I impose that the price coefficient is a decreasing function of a type's income. More specifically, the price coefficient of type d is modeled as $\gamma^d = \frac{\alpha}{\log(y^d)}$

Across time and local markets, wireless carriers can differ substantially in various quality dimensions. Such differences are often observed by the agents, but not by the econometrician. In the model, they are captured by ξ^d_{jmt} which is a real-valued unobserved vertical characteristic. I assume that ξ evolves according to an exogenous $AR(1)$-process with a mean-zero innovation ν:

$$\xi^d_{jmt} = \iota \xi^d_{jmt-1} + \nu^d_{jmt}$$

where ι is a nuisance parameter to be estimated. Such a specification is justified by noting that typical components of ξ, like brand-reputation, customer service and unobserved components of carriers' infrastructure are very persistent across quarters. ϵ^i_{jmt} is an *iid* logit shock drawn from a type-1 extreme value distribution capturing individual-specific shocks to the utility from each product.

ψ^d represents a consumer's switching cost that has to be paid once she decides to be on a different network in the current period than in the previous period. It comprises all hassle costs associated with the switching process, i.e. transaction costs for canceling a subscription, explicit early termination and start-up fees, costs of buying new equipment and potential learning costs. If applicable, *poaching payments*, i.e. one-time payments made by an operator to whom a consumer switches, for example in the form of handset subsidies, reduce the switching costs. Therefore, ψ^d should be interpreted as a net switching costs. Moreover, I do not distinguish between quitting and start-up costs. As the definition of my outside good does not allow consumers to be in a switching cost free state, I assume that all switching costs are paid when quitting an operator's service. Although ψ^d may in principle differ across markets and products, I treat it as constant in those dimensions.

The network effect operates through $s_j^{r_d}$, the market share of operator j in the reference group of consumer d. If affects a consumer's utility in two ways. First, it explicitly lowers a consumer's monthly bill because a higher network size generally implies a lower need for buying more expensive off-net minutes. Second, as argued in Section 2, consumers may derive explicit additional utility from being on a larger network. The parameter α^d will capture the sum of all these effects after controlling for the average price per minute and usage quantity. In Appendix A, I show how the price effect associated with network size can be disentangled from other network effect components when additional data are available.

In the context of network effects, the specification of the reference group is crucial. In principle, the reference group can be specified by an arbitrary interaction of local market and observed demographic characteristics. Identifying restrictions on the composition of the reference group to overcome the reflection problem are discussed in Section 2.5.1. For the empirical application, I assume that a consumer's reference group consists of all consumers in her local market m. This assumption is plausible as for many people, their social network is likely to be localized within their home region.[4] There is also empirical evidence on the local market being an important reference group. For example, a report from Teletruth, a consumer advocacy group, indicates that in 2008 local calls made up two thirds of an average phone bill.

As I analyze anonymous network effects, I assume that each demographic group d consists of a continuum of consumers so that individuals do not act strategically but take the equilibrium as given. The timing of consumer decisions between periods $t-1$ and t is as follows:

1. Each consumer i observes the industry structure $\Omega_t = (X_t,\, \xi_t, s_{t-1})$ and his idiosyncratic shock ϵ_{it}.[5]

[4] Similar ideas underlie Hoernig, Inderst, and Valletti (2014), Birke and Swann (2006) and Maicas, Polo, and Sese (2009).

[5] Implicitly, this specification abstracts from problems of limited information as in Sovinsky Goeree (2008). In my model, people are perfectly informed about product characteristics and prices.This information structure can be justified by noting that wireless carriers heavily engage in advertising and marketing so that consumers can get an accurate picture of the market environment easily.

2. Given (1), consumers form rational expectations on the choices of consumers in their reference group: $\mathbb{E}[s_{jt}^{r_d}|\Omega_t] = \int_{i' \in r} Pr(a_{i't} = j) dG(i')$. Given the assumption of a continuum of consumers, there is no uncertainty in the aggregate so that rational expectations are equivalent to perfect foresight consumers.

3. Based on their expectations from (2) consumers simultaneously choose their utility maximizing alternative. Market shares s_t and churn rates c_t are realized such that the observed market shares are the outcome of a *self-consistent equilibrium* (Brock and Durlauf 2003) and one of possibly several fixed points of a mapping Ψ that maps the industry structure and expectations on market shares into realized market shares ($s_t = \Psi(\Omega_t, \mathbb{E}[s_t])$)

This timing and information structure provides a justification for using observed market shares as measures for consumers' expectations on network size. The presence of social effects is likely to result in the existence of multiple equilibria which can be a severe problem for identification and estimation. Therefore, I assume that within each reference group, consumers coordinate on a single equilibrium. In my application, this assumption can be justified: I analyze the industry in a mature stage, so that consumers plausibly had enough time to learn about the market environment and coordinate successfully. This assumption is less restrictive than the often-used *single-equilibrium in the data* assumption as my framework allows different reference groups, for example different local markets, to play different equilibria.

The structure of the model and the distribution of the *iid* error term result in closed-form solutions for consumers' conditional choice probabilities as a function of mean flow utilities δ and the switching cost parameters ψ:

$$Pr^i(\text{not switch}) = Pr^i(j|j) = \frac{\exp(\delta_{jt}^i)}{\exp(\delta_{jt}^i) + \sum_{l \neq j} \exp(\delta_{lt}^i - \psi^i)}$$
$$Pr^i(\text{switch from } k \text{ to } j) = Pr^i(j|k) = \frac{\exp(\delta_{jt}^i - \psi^i)}{\exp(\delta_{kt}^i) + \sum_{l \neq k} \exp(\delta_{lt}^i - \psi^i)}$$

Consequently, market shares and churn rates can be computed recursively:

$$\begin{aligned} s^i_{jt} &= \sum_{j'} P^i(j|j')s^i_{j't-1} \\ c^i_{jt} &= 1 - Pr^i_t(j|j) \end{aligned}$$

These predictions can be taken to the data to form moment conditions.

2.4 Data

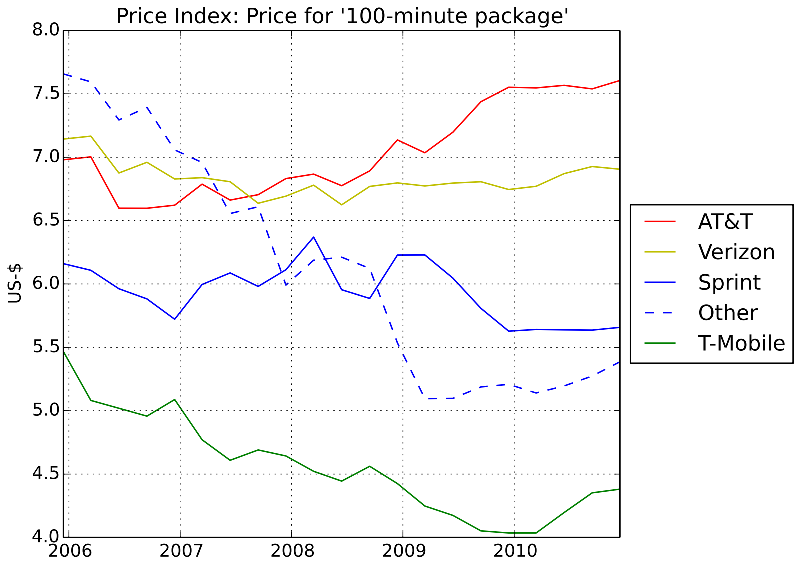
To estimate the model, I combine group-level panel data constructed from a large-scale repeated cross-section survey and operator-level statistics from the Global Wireless Matrix, an industry report by Merrill Lynch Research. The sample period is from January 2006 to December 2010.

Global Wireless Matrix The Global Wireless Matrix contains quarterly data on operational and accounting figures for the major 4 carriers as well as the most important regional operators. These are not broken down by regional market, but only available on the national level. I use these data to construct average price indices for each operator and quarter from aggregate usage and revenue data. In addition, I consider information on the cost side, in particular EBITDA (earnings before interest, taxes, depreciation, and amortization) and revenue data to construct instruments for the subscription prices charged by operators.

Survey data My main data source is a survey conducted quarterly by Comscore, a market research firm. It surveys more than 30,000 cellphone users throughout the US in each quarter. The survey is stratified in order to allow for a representative projection for the whole US market. It contains detailed information on the operator choice of individual consumers as well as their demographic characteristics such as age, income, ethnicity or employment status.

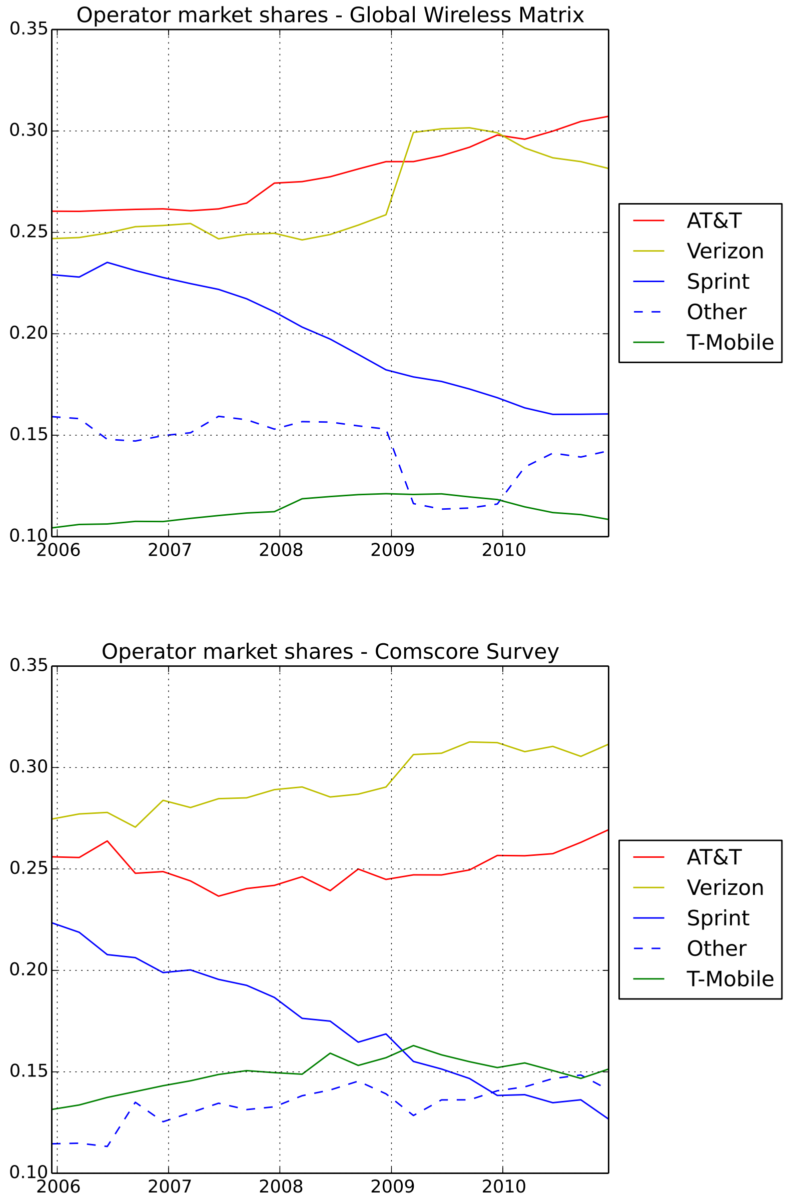
Information on the specific contracts chosen by individuals is limited to the type of contract (individual, family plan, prepaid) and the monthly expenditure for the wireless bill. Unfortunately, the data do not contain detailed information on the

Figure 2.1: Constructed price index



specific pricing structure of each contract. Previous papers on the wireless industry have mostly assumed individuals to consume identical quantities and taken the average revenue per user as price to be paid. I improve upon the existing approaches by constructing a price index for an average service bundle, for example a 100-minute package on a particular network j in quarter t. More specifically, using the firm-level data from the Global Wireless Matrix, I divide *Average Revenue per User* by *Average Minutes-of-Use* for each quarter-operator observation to get a price index p_{jt}. The resulting price index is displayed in Figure 2.1. The resulting proxy for monthly subscription price still abstracts from the complicated two-part pricing schemes observed in the telecommunications industry. However, it seems to be consistent with anecdotal industry evidence. For example, the price index is significantly higher for AT&T and Verizon who usually offer higher quality service at higher prices while T-Mobile which is known for pricing more aggressively has the lowest price index. Franchetti (2014) argues that given the plethora of different pricing structures, an average price index may actually be what consumers take into account most. Assuming that every consumer faces the same average price, I can compute the average usage quantity of each consumer by dividing total expenditure by the price index. For simplicity, I treat this usage quantity as fixed throughout the estimation and the counterfactuals. One could extend the model to a continuous-discrete choice framework as in Schiraldi, Seiler, and Smith (2011) by modeling quantity as the

Figure 2.2: Comparison of market shares: survey sample vs. GWM



outcome of a static optimization problem.

Consumers are also asked about their switching behavior, in particular how long a consumer has been subscribed to her current operator. If a respondent reports being subscribed to her operator for less than 3 months, I treat this consumer as having switched in this period. There is also a question about their previous operator. Unfortunately, only very few consumers respond to this question. Consequently, I cannot reliably construct the full matrix of conditional choice probabilities. Therefore, I develop an estimation strategy that relies only on unconditional choice probabilities contained in the market shares and the subset of the conditional choice probabilities contained in the churn rates.

Summary statistics of the survey respondents' characteristics split up by four consumer types are displayed in Table 2.1. The first two columns display consumers' age (in years) and yearly household income (in US-$ 1,000) followed by the monthly expenditure for wireless plans (in US-$). *MoU100* displays how long survey respondents use their cellphone per month (in 100-minutes). The last column contains information on what fraction of people switch their operator within a month.

Table 2.1: Descriptive statistics: Consumer type characteristics

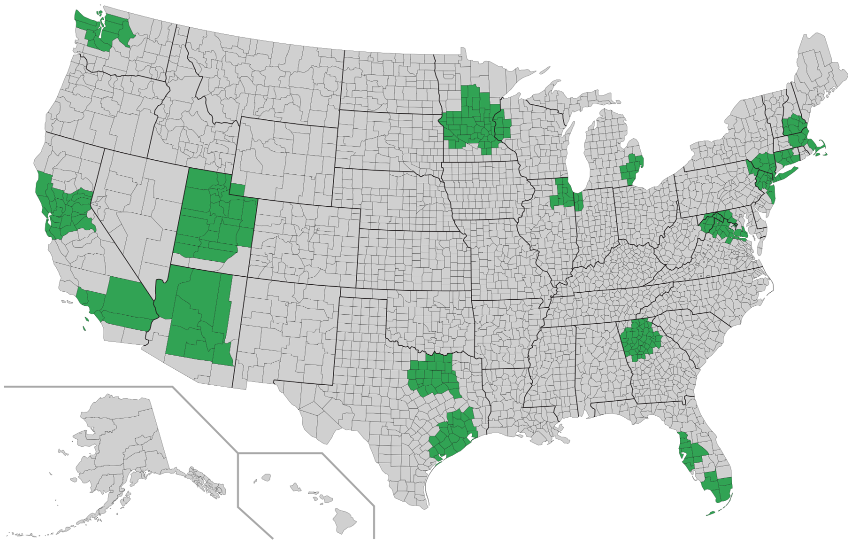
ctype	Statistic	Age	Income	Expenditure	MoU100	Switch
>45 years-poor	Mean	56.24	29.33	53.08	8.70	0.03
>45 years-poor	SD	13.45	11.73	32.71	5.63	0.16
>45 years-rich	Mean	53.41	87.89	69.75	11.02	0.02
>45 years-rich	SD	12.34	21.59	32.49	5.41	0.13
<45 years-poor	Mean	24.00	27.50	66.32	11.13	0.05
<45 years-poor	SD	5.61	12.25	31.37	5.78	0.22
>45 years-rich	Mean	24.23	84.10	73.45	11.88	0.03
>45 years-rich	SD	6.18	21.11	30.93	5.43	0.18

Finally, the survey contains information on consumers' satisfaction with the quality of the provided wireless service rated on a scale from 1 to 10. In my estimation, operator fixed effects control for differences in the national mean of quality characteristics. To control for variation in local coverage quality, I use information on the average satisfaction level of all customers of an operator within a local market as proxy for this operator's network quality in this region. This variable does not necessarily capture physical signal quality but rather an aggregate index of perceived service quality by a particular type of consumer. Kim, Park, and Jeong (2004) and Kim and Yoon (2004) provide evidence that in the Korean market customer satisfaction and call quality are highly correlated.

In using these variables, I cannot rule out biased reporting due to consumer selection. For example, more demanding consumers may choose higher quality operators but may also be more critical in rating service quality. To solve this problem, I do not use the absolute level of satisfaction, but take the normalized deviation of the average rating within a region by a specific consumer type d from the national average rating of this type-operator combination. As the fixed-effects capture operators' mean quality level, the satisfaction deviation measure should appropriately control for regional variation in service quality. Descriptive statistics of the original satisfaction variable and the constructed proxy for local coverage quality are summarized in Table 2.17 in Appendix B.

Unfortunately, the survey is not a panel, but a repeated cross-section. This limits the possibilities for using the individual-level data directly to analyze demand dynamics. Therefore, I construct a panel of demographic group-specific market shares. For data availability reasons, I focus on four consumer types (see Table 2.2) and the biggest local markets (see Table 2.18 in the Appendix). This leaves me with 20 geographically separated markets consisting mostly of the urban areas around the largest US cities. These markets differ in several respects, for example in their local age or income distribution. However, they are relatively similar in other dimensions, like the degree of urbanity, the wireless penetration rate (of almost 100%) or market size. Therefore, I expect market size effects not to play a significant role. As I exclude very rural areas, the market shares constructed from the survey differ slightly from the market shares reported in aggregate industry reports. However, the differences are plausible, for example AT&T which is relatively strong in some less densely populated areas has a lower market share in my sample while T-Mobile which focuses on densely populated urban markets has a higher market share in my sample. The geographical size and distribution of the local markets is illustrated in Figure 2.3.

Figure 2.3: Overview of local markets used in the estimation



2.5 Identification and estimation

2.5.1 Identification

In this subsection, I show under which assumptions the parameters of the demand model are identified. In particular, I show how switching costs and localized network effects can be disentangled from preference heterogeneity and that the reflection problem does not occur under certain conditions.

Consumer heterogeneity in the form of consumer type-specific coefficients is identified by differences in type-specific market shares. As in Berry, Levinsohn, and Pakes (1995), variation in the choice sets across local markets and time identifies type-specific price and quality coefficients. For separately identifying switching costs and network effects, I rely on two key assumptions that are implicit in my model:

Assumption 2.5.1. *Conditional on a consumer type d, consumers have homogeneous preferences. Preferences are constant across time or local markets (or both).*

Assumption 2.5.2. *Each consumer has one reference group r_d the average behavior of which she takes into account. Neither the determinants of r_d nor the determinants of d are a (weak) subset of the other.*

As in Yang (2010), the key data to identify switching costs are churn rates. The model's churn rate predictions are given by one minus the conditional choice probabilities of sticking to a product. This subset of the conditional choice probabilities contains more detailed information than the unconditional choice probabilities implicit in the market shares. Under Assumption 2.5.1, this allows for comparing the choice probabilities of consumers with identical preferences but different choices in the previous period: If switching costs are zero, the unconditional choice probabilities should be identical to the conditional choice probabilities. Positive switching costs will drive a wedge between the two which will identify switching costs.

The identification of network effects is more complicated and runs into several problems. First, similar to the well-known endogeneity problem of price, reference group market shares will be correlated with the unobservable demand shocks which requires finding appropriate instruments. After normalizing for usage quantity and redefining the mean flow utility per unit, $\delta^d_{jmt} = \frac{\delta^d_{jmt}}{q^d_{jmt}}$ can be decomposed as:

$$\delta^d_{jmt} = X^d_{jmt}\beta^d + \gamma^d p^d_{jt} + \alpha^d s^{r_d}_{jmt} + \xi^d_{jmt} \tag{2.1}$$

where d, j, m and t index consumer type, operator, local market and time respectively. Valid instruments for $s^{r_d}_{jmt}$ have to be correlated with the endogenous regressor but uncorrelated with the unobserved error term. An additional problem arises, because mean utilities are not observed in the data. As in the literature on pure switching cost models (Shcherbakov 2013; Nosal 2012), they have to be inferred from market share data. Knowing the contemporaneous market shares s_{mt} and previous period's market shares for type d is sufficient for computing the values of type d's mean utilities in market m and period t (δ^d_{mt}) so that $\delta^d_{jmt} = f(s_{mt}, s^d_{mt-1})$. The instruments for reference group market shares must not enter equation 2.1 directly, in particular the market share variables needed to back out δ^d_{mt} cannot be used as instruments. If these were the only available shifters of $s^{r_d}_{jmt}$, the reflection problem would occur in equation 2.1 and network effects could not be identified.

My key assumption for identifying a localized network effect is Assumption 2.5.2. Intuitively, this assumption requires two things: First, a reference group characteristic that allows one to observe individuals with identical preferences in different network environments. The prime example for such a characteristic is the local market. The second requirement is that there is some heterogeneity across the consumers within a reference group. This heterogeneity can be used to construct the necessary exclusion restrictions and instruments: With $-d$ denoting all consumer types within d's reference group except for d itself, the reference group market share for type d is a function of the lagged market shares of types d and $-d$ as well the weights (D_{mt}) of the different demographic types in her market.

While s^{-d}_{mt} shifts the mean utility for type d in period t directly, $s^{r_d}_{mt-1}$ is excluded from the utility of type d in period t. Lagged market shares of type d affect s^d_{mt} and δ^d_{mt} through both the switching costs as well as the network effect. Therefore, looking at own-type lagged market shares will not be sufficient to separately identify the network effect α. In contrast, s^{-d}_{mt-1}, will affect s^d_{mt} only if there is a network effect. This motivates using lagged market shares of types $-d$ as instruments for current period's reference group market shares for type d. These variables are correlated with $s^{r_d}_{mt}$ as long as there is some sort of state-dependence in consumer choices. Lagged market shares of types $-d$ would be uncorrelated with ξ^d_{mt} if the ξ-terms were either uncorrelated across demographic groups or time periods. However, it is likely that the unobserved quality characteristics are correlated in both dimensions. To construct valid moment conditions, I exploit the dynamic panel data structure by interacting the instruments from lagged periods with contemporaneous values of ν, the exogenous innovation in the ξ-process, instead of its levels.

Intuitively, one can think of the identification strategy as comparing the behavior of the same consumer type d under the dynamics of different network environments. In my application the variation in networks occurs over time and local markets. Local markets differ with respect to the initial conditions, the evolution of local service quality and the distribution of demographic characteristics D_{mt}.

The initial conditions reflect different market histories that cause operators to start the sample period with different network sizes in different markets. These different histories contain variation due to exogenous differences across operators and local markets, for example in spectrum availability, tower and antenna locations or regulation of land use.

Furthermore, local markets differ in the evolution of operators' local service quality. I assume that this evolution is determined by an exogenous technological process. Across different markets, different operators roll out specific service features differently across time. This may result in different consumer types evaluating the stand-alone service quality of an operator within a market differently. As described in Section 2.4, I capture type-specific perceived quality with a proxy based on the survey's satisfaction measure. While the effect of a type's own perceived quality will be informative about her valuation for quality, the perceived quality of other types in her reference group will help identifying the magnitude of the network effect. To consider an illustrative example, assume that only younger consumers care about high data speed. If AT&T can roll out its LTE network in New York, but not in Georgia, comparing the reaction of the older consumers in the two markets should contain information on the strength of the network effect.

Finally, demographic distributions D_{mt}, such as the age and income distribution, are plausibly exogenous and vary across local markets and time. Variation in the demographic composition will lead to different weightings of the distinct types within a reference group. These weightings make two markets with the same quality characteristics different and so introduces additional exogenous variation which shifts reference group market shares.

A few remarks on the potential breakdown of my identification strategy are in order. The second part of Assumption 2.5.1 states that consumers' preferences do not change either over time or across local markets. If my model allowed for systematically different consumer preferences in both dimensions, one could perfectly explain a higher market share in some market by a change or differences in preferences for a particular operator in that market. This implies that I can allow for market- or time-specific preferences but not both. In my application, I control for consumer heterogeneity in the arguably most important dimensions, age and income.[6] Therefore the assumption that consumers have identical preferences across local markets and time can be justified.

Moreover, my identification approach would fail, if consumers' reference groups consisted only of their own type as then the set of exclusion restrictions and instruments based on types $-d$ would be empty. This is a restrictive assumption that prohibits me from identifying all potential kinds of network effects.

A particularly delicate issue is to separate network effects from the effects of unobserved quality differences. Even though I control for local service quality in a broad sense, one may argue that there are additional unobserved characteristics that I am not able capture in the data. Such attributes may also comprise advertising intensity or promotion activities. In that case, one may worry that my estimates of the network coefficients pick up the effects of these unobservables. To see how I

[6] My data is rich enough to conduct additional robustness checks in this dimension. For example one could have preferences differ across ethnicities, education or employment status.

mitigate this problem, note that any unobserved quality attribute, call it υ^d_{jmt}, will enter into the structural demand error $\tilde{\xi}$.

$$\delta^d_{jmt} = X^d_{jmt}\beta^d + \gamma^d p_{jt} + \alpha^d s^{r_d}_{jmt} + \underbrace{\upsilon^d_{jmt} + \xi^d_{jmt}}_{\tilde{\xi}^d_{jmt}}$$

Consequently, $s^{r_d}_{jmt}$ will be correlated with $\tilde{\xi}^d_{jmt}$. Using moments based on the first-differenced equation will control for all persistent differences in unobserved quality across local markets, for example a constantly high advertising intensity of some operators in some markets.

$$\Delta\delta^d_{jmt+1} = \Delta X^d_{jmt+1}\beta^d + \alpha^d \Delta s^{r_d}_{jmt+1} + \underbrace{\nu^d_{jmt+1}}_{\Delta\xi^d_{jmt+1}+\Delta\upsilon^d_{jmt+1}}$$

While $\Delta s^{r_d}_{jmt+1}$ will still be correlated with ν^d_{jmt+1}, lags in levels and first-differences of other types' market share distributions can be used as instruments. Due to the sequential exogeneity assumption on ν, the instruments will be uncorrelated with the error term ν_{t+1}.

The implications of the sequential exogeneity of ν are twofold. First, it is crucial that ν_t contains only factors that cannot be anticipated by consumers before t. In the wireless industry, this is not unreasonable. Typical components of ξ and ν are brand reputation and the introduction of new service features that often have properties of experience goods. Innovations to these characteristics are usually hard to evaluate before they are actually realized. In contrast, easily verifiable characteristics like information on coverage quality (towers and antennas), new handsets or subscription prices are captured by the observables X which are explicitly controlled for.

A second assumption is that ν cannot be chosen or influenced by firms based on market characteristics. This would however be the case if firms react to their market position by adjusting any (unobserved) component of ν. For example, identification would break down if one allows firms to adjust unobserved quality levels or advertising intensity based on the instruments used for network size. This would lead to a correlation between the instruments and the unobserved error term even in first-differences, as then $\Delta\upsilon^d_{jmt+1} = f(s^{-d}_{jmt-1}, D_{mt-1})$. In general, one can alleviate this problem by imposing an additional timing assumption on firms' strategies. One could assumes that firms choose ν_{t+1} only based on the most recent realization of the state variables in period t. Using instruments based on realizations of the state variables in period $t-1$, will then deliver valid moment conditions. If one is concerned about the effects of advertising or store infrastructure specifically, one could incorporate explicit data on operator's marketing intensity across different local markets and over time.[7]

2.5.2 Estimation

The estimation routine consists of three steps. In the first step, I back out the mean utilities similarly to BLP by matching predicted to observed market shares. The type-specific market shares in my model can be written as:

$$s^d_{jmt} = \sum_{j'} Pr^d(j|\delta^d_{mt}, a^d_{t-1} = j') \cdot s^d_{j'mt-1}$$

where a_{t-1} denotes a consumer's choice in the previous period. The conditional choice probabilities for type d are a function only of the mean utilities of type d (δ^d) and the switching cost parameter ψ^d:

$$Pr^d(j|\delta^d_{mt}, a^d_{t-1} = \bar{j}) = \frac{\exp(\delta^d_{jmt} - \mathbb{1}_{j\neq\bar{j}}\psi^d)}{\sum_{j'} \exp(\delta^d_{j'mt} - \mathbb{1}_{j'\neq\bar{j}}\psi^d)} \quad \forall d, j, m, t$$

When implementing the estimation, I use an iterative mapping similar to BLP. Conditional on the structural parameters θ, I solve for a fixed point of:

$$f(s_t, s_{t-1}, \theta)\,[\delta_t] = \delta_t + \log(s_t) - \log(\mathscr{S}_t(s_{t-1}, \theta, \delta_t)) \tag{2.2}$$

where s_t and $\mathscr{S}_t$ denote observed and predicted market shares respectively. In contrast to the standard BLP-mapping, I take into account the presence of switching costs and network effects. Switching costs imply that I have to solve for market share predictions recursively period-by-period. In addition, I ensure that upon convergence of the predicted and observed market shares, market share predictions are consistent with the structure of the mean utilities decomposed into a standalone utility $\hat{\delta}$ and utility from the network effect: $\delta^d_{jmt} = \hat{\delta}^d_{jmt} + \alpha^d s^{r_d}_{jmt}$ with $s^{r_d}_{jmt} = \sum_{d' \in r_d} w^{d'}_{mt} s^{d'}_{jmt}$ being a weighted average of the actual predicted market shares of the different types in a market. As upon convergence of the mapping, observed and predicted market

[7] These data are for example available in the Ad$pender data base by Kantar Media.

shares are identical, this is equivalent to plugging in observed market shares. The classical proof of BLP can be extended to prove the existence of fixed point of equation 2.2. However, as in the literature on dynamic demand estimation, one cannot formally prove uniqueness using BLP's arguments.[8]

Conditional on the resulting vector of mean utilities, I compute a churn rate prediction error ζ, i.e. the difference between predicted and observed churn rates:

$$c^d_{jmt} - \mathscr{C}^d_{jmt}(\delta_t, \psi) = \zeta^d_{jmt} \tag{2.3}$$

Afterwards, I directly form moment conditions based on ζ and include them into the criterion function. Consequently, I treat ζ as a nonstructural error term that comprises structural parts as well econometric overfitting error. I choose this specification because in my data churn rates are likely to be measured with error. Most problematic is that on a very disaggregated level some churn rates in the data are zero. The structural model will never predict this unless switching costs are infinity.[9]

In the second step, I decompose the mean utilities to back out the structural error terms ξ and ν:

$$\rightarrow \xi^d_{jmt} = \delta^d_{jmt} - X^d_{jmt}\beta^d - \gamma^d p^d_{jmt} - \alpha^d s^{r_d}_{jmt} \tag{2.4}$$

$$\rightarrow \nu^d_{jmt} = \xi^d_{jmt} - \iota\xi^d_{jmt-1} \tag{2.5}$$

In the final step, I use the method of GMM to estimate the parameters. The set of moments used is based on interacting the error terms ξ, ν and ζ with appropriate

[8] In robustness checks, I searched for fixed points of equation 2.2 starting from several different starting values and always converged to the same solution.

[9] Two ad-hoc solutions for this measurement error or *zero-problem* would be to treat the zero observations as missing values and impute these values or to simply aggregate the observed churn rates up to a level where the zero-problem does not occur anymore. This would allow me to proceed as in Yang (2010). He uses a double contraction mapping to back-out mean utilities and the switching cost for each observation.

instruments Z:

$$E[G^1(\xi, Z^1)|\Theta_0] = 0$$
$$E[G^2(\nu, Z^2)|\Theta_0] = 0$$
$$E[G^3(\zeta, Z^3)|\Theta_0] = 0$$

Moments based on ξ will identify quality and price coefficients with Z^1 containing operator dummies, exogenous product characteristics as well as instruments for subscription prices. The network effect will be backed out interacting ν with instruments (Z^2) based on the exclusion restrictions discussed in the previous subsection. The last set of moments exploits the churn rate prediction error ζ. Because of its nonstructural character ζ can be interacted with the superset of all instruments used in Z^1 and Z^2.

To solve the typical endogeneity problem of price, I instrument subscription prices p_{jt} using cost side information. Similar to Yang (2010) I use firms' revenue and EBITDA to compute a proxy for short-run variable costs. I use short-run variable cost per subscriber as an instrument. A drawback of cost side data is that it is only available on the national level, and does not exhibit a lot of variation. Therefore, I include additional instruments based on the average characteristics of operators' subsidized handset portfolio (BLP-instruments). The attractiveness of competitors' handset portfolios shifts an operator's price-cost margins and is therefore a valid instrument for price.

Based on the logic of the exclusion restrictions discussed in the previous subsection, I instrument the reference group market share relevant for type d ($s^{r_d}_{jmt}$) with the lagged market shares among other types than d in d's reference group, weighted by their demographic mass:

$$Z^d_{jmt} = \sum_{d' \in r_d, d' \neq d} s^{d'}_{jmt-1} \cdot D^{d'}_{mt-1}$$

In a myopic model, the values of Z^d_{jmt} are fully determined in $t-1$. So by definition they must be uncorrelated with ν_{t+1}. Moment conditions in the form of $\mathbb{E}[Z^d_{jmt} \cdot \nu^d_{jmt+1}]|\theta_0] = 0$, should therefore be valid and be sufficient to identify the network effect. Similar moment conditions are used in Lee (2013) and Schiraldi (2011) in slightly different contexts. Arellano and Bover (1995) and Blundell and Bond (1998) demonstrate that using both lagged variables in levels as well as first-differences is much more powerful than relying on instruments in levels alone. Therefore, I use first (pseudo-)differences in Z^d_{jmt} additionally. Analogously, I could include the perceived quality ratings of other types as instruments. Controlling for the perceived quality of type d directly, the ratings of other types should only affect the mean utility of types $-d$ through the network effect. In my application, adding these moments did not significantly alter the results.

Specification details For the main estimation I choose the following specification: $d = \{\text{age}\} \times \{\text{income}\}$, both measured in a binary way. Consequently, I allow for four different consumer types as describd in Table 2.2. A consumer's reference

Table 2.2: Overview of consumer types

d	Age	Income
1	>45	below median income
2	>45	above median income
3	<45	below median income
4	<45	above median income

group consists of all individuals in her home region, i.e. r_d = (local market) and so comprises 4 different consumer types and each consumer within a local market faces the same reference group. One can narrow down the definition of the reference group by defining it on an interaction of local market and either age or income characteristics.[10] Refining consumers' reference groups further to a narrowly-defined demographic group, for example to an interaction of age, income and ethnicity can lead to two problems. First, from an empirical perspective it is hard to construct reliable estimates of narrow demographic-group specific market shares even with an enormous amount of observations. Second, one may question that an individual's reference group consists only of consumers that are of exactly the same type. For example, family members might be in a different age group, friends may have a different ethnicity or fall into a different income group.

I treat preferences as constant across time and local markets. The set of observable

[10] Qualitatively, the results for these specifications did not differ from the baseline specification.

product characteristics X^d_{jmt} includes nation-wide operator-fixed effects, an iPhone fixed effect that is equal to one for the quarters in which AT&T exclusively offered the iPhone on its network. In addition, proxies for local service quality and the number of exclusively available smartphones on an operator's network are used. The latter variable should capture the attractiveness of an operator's subsidized handset portfolio. As I have only limited pricing and contract data I have to make simplifying assumptions on the composition of consumers' monthly expenditure: I assume that consumers pay according to a linear pricing scheme. As discussed in Section 2.4, I construct the price index such that monthly expenditure is perfectly explained by $R^i_{jt} = p_{jt} \cdot q^i_{jt}$. Throughout the estimation and the counterfactuals, I use the observation weights to correct for the survey's stratification when aggregating across types and markets.

Multiplicity of equilibria A well-known problem with models of social interactions is that there may be multiple equilibria. My setup differs from the multiplicity issues that typically occur when dynamic games are estimated using two-step methods or when choice probabilities are used directly to construct likelihood functions. In my estimation routine, I back out a vector of mean utilities by inverting the market share equation market-by-market. I do not pool market shares before doing the inversion step: In case of equilibrium multiplicity, the market share mapping may be a correspondence with multiple predictions for s_{mt}. However, each of these predictions will be associated with a different mean utility vector.

As I assume that there is no coordination failure and that the observed market shares come from an equilibrium, I know from the data which equilibrium is played in each market. I back out only the mean utility vector associated with the equilibrium actually played. I pool the mean utilities of all markets only in the second step when decomposing the mean utilities in the effect of the different factors such as quality, price or network effects conditional on a particular equilibrium being played. In this step, multiplicity of equilibria may actually help in identifying the network effect because it introduces an additional source of variation into the model. Therefore, multiplicity of equilibria across different markets will not be problematic for the estimation. However, for doing counterfactual analysis, the issue persists. A computational intensive, but feasible solution is to try to compute all equilibria starting from different consumer beliefs and so get bounds on measures such as welfare gains or simulated market share distributions.

2.6 Results

Tables 2.3 and 2.4 display the results for the myopic logit model. The last column translates the coefficients into monetary willingness-to-pay using the marginal utility of money derived from the estimated price coefficient. For the switching costs, the last column displays the monetary equivalent of a one-time utility loss from switching operators once. For the network effects, it displays the average monthly willingness to pay for an increase of an operator's market share within a consumer's reference group by 20 percentage points. Almost all coefficients have the expected sign

Table 2.3: Results for myopic model (non-linear parameters)

	Point Estimates	Standard Error	P-Values	WTP in US-$
Network effect, d=1	0.3336	0.0046	0.0000	18.87
Network effect, d=2	0.2537	0.0085	0.0000	24.05
Network effect, d=3	0.2537	0.0076	0.0000	17.98
Network effect, d=4	0.2551	0.0137	0.0000	25.81
Switching cost, d=1	3.2107	0.1454	0.0000	316.77
Switching cost, d=2	4.8007	0.1959	0.0000	626.30
Switching cost, d=3	4.5503	0.1971	0.0000	439.77
Switching cost, d=4	2.9879	0.2948	0.0000	385.88

Table 2.4: Results for myopic model (linear parameters)

	Point Estimates	Standard Error	P-Values
Local service quality, d=1	0.0023	0.0002	0.0000
Local service quality, d=2	-0.0022	0.0003	0.0000
Local service quality, d=3	0.0108	0.0035	0.0021
Local service quality, d=4	0.0091	0.0036	0.0120
Log(subscription price), d=1	-0.0618	0.0242	0.0108
Log(subscription price), d=2	-0.0468	0.0183	0.0108
Log(subscription price), d=3	-0.0631	0.0248	0.0108
Log(subscription price), d=4	-0.0472	0.0185	0.0108

and are highly significant. Local service quality enters with a positive coefficient for all types except for type $d = 2$ (>45, above median income). The estimates for network effects imply reasonable magnitudes in terms of willingness-to-pay: For an

Table 2.5: Overview on consumer types and average expenditure

d	Age	Income	Monthly expenditure
1	>45	below median income	US-$ 53
2	>45	above median income	US-$ 70
3	<45	below median income	US-$ 66
4	<45	above median income	US-$ 73

increase in an operator's local market share by 20 percentage points, which is the typical difference in market shares between one of the two big operators and the smaller ones, consumers would be willing to pay between US-$ 18 and US-$ 26 per month with richer consumers paying more attention to network size than the poor consumers. Compared to the average quarterly expenditure for wireless plans in the US (cf. Table 2.5), my estimation suggests that network effect account for almost 30% of expenditure. This seems large, but comprises the compound effect of all potential channels through which network effects may operate (after controlling for average price differentials across operators). In Appendix A, I outline how one can decompose this effect further if additional data are available.

Finally, the estimates reveal that switching costs are large and very heterogeneous across consumer types. For $d = 1$ (>45, below median income) switching costs are lowest (US-$ 317), most likely because these consumers often have a very basic plan that is easy to transfer to another operator. For $d = 2$ (>45, above median income) who often have large plans that comprise several lines and devices, switching costs are highest (US-$ 626). For younger consumers, switching costs are more homogeneous and on average a bit lower. Interestingly, $d = 3$ (<45, below median income) have lower switching costs than $d = 4$ (<45, above median income). This may be due to consumers of the latter type often having the most expensive handsets. The fact that subsidies for handsets effectively reduce the switching costs, can explain the higher switching cost for poorer young consumers. Relatively speaking switching costs are roughly on the order of 6 to 9 months' average expenditure.

To get an idea on how the magnitudes of switching cost and network effects relate to each other, consider the following back-of-the-envelope calculation: A customer of one of the large carriers compares her current operator with another operator with the same quality but 20 percentage points lower market share. In order to switch to the small operator this customer will require a discount that compensates for switching costs to be paid immediately and the accumulated benefits from network size over the consumer's time horizon. Assuming that the consumer cares about the next 2 years, my estimation results imply that this discount would range between US-$ 700 and US-$ 1200 depending on the consumer type. Roughly 50% of the discount would compensate for the switching costs, the other half for the foregone network effect.

2.6.1 Price elasticities

Both switching costs and network effects are likely to result in consumer lock-in and potentially make consumers insensitive to price increases. Because of the presence of switching costs and network effects, there does not exist a closed-form formula for the price elasticities. Computing these requires resolving the model at different levels of prices. Tables 2.6-2.8 describe the implied price elasticities in the short run (6 months), medium run (2 years) and long run (5 years). These results are based on recomputing market shares for every period after an operator has increased its price index by 10% in every period. In principle, the price elasticities may depend on which specific time periods are compared. Robustness checks looking at different time periods did not result in significantly different elasticities.

Table 2.6: Short-run price elasticities

	Other	AT&T	Verizon	Sprint	T-Mobile
$p_{\text{AT\&T}}$	0.1071	-0.1679	0.0353	0.0585	0.0743
p_{Verizon}	0.1053	0.0464	-0.1614	0.0530	0.0704
p_{Sprint}	0.1127	0.0585	0.0423	-0.2484	0.0848
$p_{\text{T-Mobile}}$	0.1010	0.0444	0.0310	0.0552	-0.3146

Table 2.7: Medium-run price elasticities

	Other	AT&T	Verizon	Sprint	T-Mobile
$p_{\text{AT\&T}}$	0.0909	-0.6830	0.2387	0.2662	0.2305
p_{Verizon}	0.0952	0.2758	-0.6144	0.3039	0.2776
p_{Sprint}	0.0723	0.2585	0.2462	-0.9551	0.2337
$p_{\text{T-Mobile}}$	0.0594	0.2106	0.1983	0.2220	-1.0536

Table 2.8: Long-run price elasticities

	Other	AT&T	Verizon	Sprint	T-Mobile
$p_{\text{AT\&T}}$	0.1305	-1.9168	1.1146	0.5416	0.4813
p_{Verizon}	0.2362	1.3067	-2.0908	0.8968	0.9393
p_{Sprint}	-0.1188	0.3949	0.6252	-2.1111	0.0698
$p_{\text{T-Mobile}}$	-0.0919	0.4556	0.7741	0.1451	-2.4705

As expected, switching costs lead to very low own-price elasticities (-0.16 to -0.31) in the short-run with elasticities for the smaller operators being larger than for the big ones. On a two-year horizon elasticities become larger (-0.61 to -1.05). In the long-run consumers react strongly to price increases with elasticities around -2. These fairly large elasticities suggest, that in the long-run consumer lock-in may actually not be as strong as suggested by the large point estimates for switching costs. The long-run cross-price elasticities are largest for the bigger operators, i.e. no matter which carrier raises its price, consumers are much more likely to substitute to one of the two large firms.

2.6.2 Comparison with restricted models

Table 2.9: Comparison with restricted models - point estimates

	Full Model	No network effects	No switching costs
Log(subscription price), d=1	-0.0618	-0.0760	0.6759
Log(subscription price), d=2	-0.0468	-0.0575	0.5112
Log(subscription price), d=3	-0.0631	-0.0776	0.6900
Log(subscription price), d=4	-0.0472	-0.0580	0.5164
Network effect, d=1	0.3336	-	1.8618
Network effect, d=2	0.2537	-	3.6584
Network effect, d=3	0.2537	-	1.9800
Network effect, d=4	0.2551	-	2.1315
Switching cost, d=1	3.2107	8.8927	-
Switching cost, d=2	4.8007	8.8677	-
Switching cost, d=3	4.5503	6.7558	-
Switching cost, d=4	2.9879	8.4559	-
J-statistic	0.0478	0.8730	1.7745

Table 2.10: Comparison with restricted models - WTP

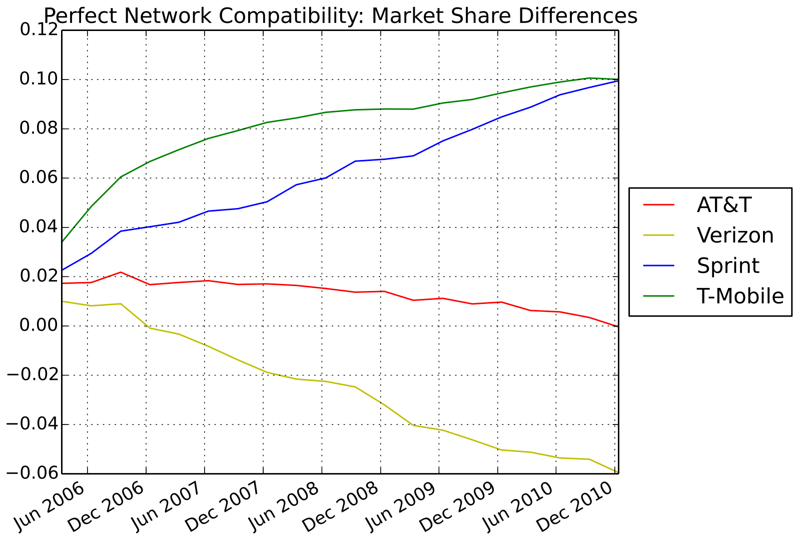
	Full Model	No network effects	No switching costs
Network effect, d=1	18.8711	-	-9.6357
Network effect, d=2	24.0523	-	-31.7323
Network effect, d=3	17.9812	-	-12.8395
Network effect, d=4	25.8078	-	-19.7294
Switching cost, d=1	316.7690	714.1376	-
Switching cost, d=2	626.2952	941.6527	-
Switching cost, d=3	439.7651	531.4504	-
Switching cost, d=4	385.8769	888.8896	-

In order to highlight the importance of being able to disentangle the effects of different sources of state-dependence, I re-estimate my model restricting either the network effects or switching costs to zero keeping everything else fixed. Table 2.9 and 2.10 display a comparison between the unrestricted model and the two restricted versions. As expected, ignoring either one of the effects results in very different and arguably implausibly large estimates of the other effects. When ignoring network effects, switching costs on average almost double which gives evidence for the fact that parts of the network effect are picked-up by the switching cost coefficient. When ignoring switching costs, the coefficients on network size increase by a factor of 10. In addition, the price coefficients become positive so that comparing monetary magnitudes becomes meaningless. Moreover, the GMM J-statistic, a measure of the violation of the moment conditions increases dramatically by a factor of 20 to 40 when estimating models that focus only on one of the two effects.

2.7 Counterfactual analyses

In a series of counterfactuals I analyze how network effects and switching costs affect consumer behavior. In particular, I evaluate consumers' price elasticities, when switching costs are regulated with the level of network effects unchanged. I contrast this setting with a situation in which switching costs remain constant, but perfect network compatibility is implemented, i.e. consumers enjoy the network effect based on the joint network size of all inside goods.

Figure 2.4: Perfect network compatibility: market share differences



Perfect network compatibility In the following, I analyze the effects of making the networks of all inside goods perfectly compatible. More specifically, I simulate the following change: Carriers charge the same average subscription prices and consumer buy the same quantities as in the observed data, but the network effect works on the cumulative market share of all inside goods.

With perfect network compatibility, price elasticities decrease significantly compared to the baseline. This is in line with Doganoglu and Grzybowski (2013) and supports the fact that network effects amplify shocks to the industry, for example due to a price increase. Own-price elasticities become only slightly more homogeneous across operators. More interestingly, cross-price elasticities become substantially more homogeneous so that under perfect network compatibility, consumers seem to substitute almost equally across operators. When looking at changes in market shares, the short-run effects of perfect network compatibility are relatively minor as switching costs prevent consumers from re-optimizing immediately. Among the major four operators the effect is monotone in network size. While AT&T's market share is basically unaffected, Verizon, the biggest carrier, loses 5 percentage points in market share until the end of the sample period. Sprint and T-Mobile gain significantly; mostly on the expense of the small operators summarized in the outside good which basically disappear after 2 years.

One should be careful in interpreting this simulation as actual policy experiments because of several limitations. Most importantly, I treat the supply side and consumers' quantity choice as fixed. Nevertheless, the demand side counterfactuals in this chapter reveal that network effects have a significant effect on consumer behavior in the wireless industry. Endogenizing consumers' quantity choice goes beyond the scope of this thesis, but is an interesting topic that I plan to pursue in future research. Chapter 4 outlines an empirical framework to endogenize firms' pricing strategies.

Table 2.11: Short-run price elasticities - perfect network compatibility

	Other	AT&T	Verizon	Sprint	T-Mobile
$p_{\text{AT\&T}}$	0.1707	-0.1639	0.0534	0.0638	0.0758
p_{Verizon}	0.1486	0.0557	-0.1589	0.0606	0.0753
p_{Sprint}	0.1638	0.0670	0.0615	-0.2290	0.0880
$p_{\text{T-Mobile}}$	0.1945	0.0625	0.0600	0.0709	-0.2873

Table 2.12: Medium-run price elasticities - perfect network compatibility

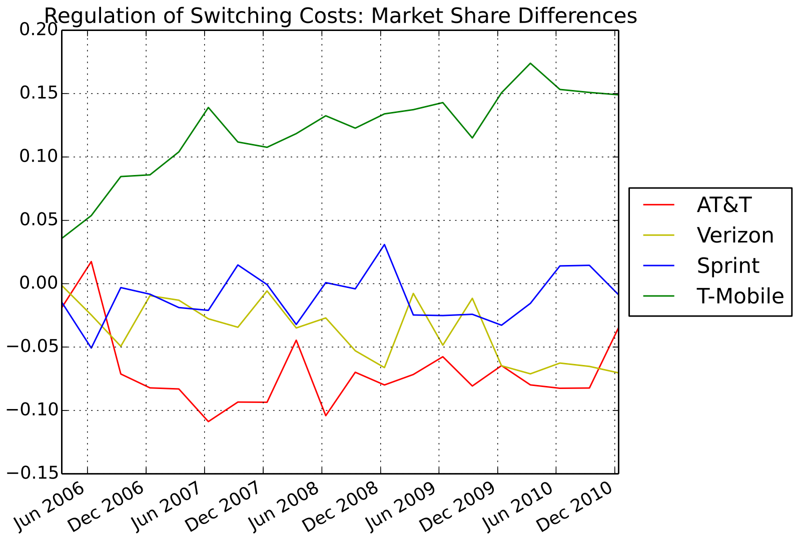
	Other	AT&T	Verizon	Sprint	T-Mobile
$p_{\text{AT\&T}}$	0.1620	-0.4236	0.1348	0.1546	0.1566
p_{Verizon}	0.1611	0.1453	-0.4145	0.1593	0.1568
p_{Sprint}	0.1655	0.1678	0.1549	-0.5397	0.1825
$p_{\text{T-Mobile}}$	0.2061	0.1830	0.1697	0.1975	-0.6047

Table 2.13: Long-run price elasticities - perfect network compatibility

	Other	AT&T	Verizon	Sprint	T-Mobile
$p_{\text{AT\&T}}$	0.1634	-0.5699	0.2041	0.2098	0.2079
p_{Verizon}	0.1501	0.2146	-0.6412	0.2162	0.2159
p_{Sprint}	0.1981	0.2281	0.2298	-0.7679	0.2426
$p_{\text{T-Mobile}}$	0.2721	0.3025	0.3019	0.3247	-0.9405

Reduction of switching costs There are several ways one could think of policy measures to reduce consumer switching costs. A regulator could prohibit early-termination fees, or force operators to provide a transparent switching procedure.

Figure 2.5: Regulation of switching costs: market share differences



From an operator's point of view, consumer switching costs could be overcome by subsidizing switching, for example in the form of poaching payments. A scenario in which switching costs are completely eliminated is very unrealistic as consumers will always incur hassle costs and opportunity costs of time when switching providers. Therefore, I analyze the effect of a reduction of switching costs by 50% which would be equivalent to a switching subsidy of roughly US-$ 150 to US-$ 300 (depending on the consumer type).

Compared to the baseline elasticities, consumers react much more strongly and quickly to a price increase. Short-run elasticities triple, while medium-run elasticities almost double. The difference between medium- and long-run elasticities basically disappears. Heterogeneity in own-price elasticities across operators measured by the difference between the largest and smallest elasticity increases by a factor of 2 when switching costs are decreased.

Not surprisingly, market shares become more volatile in the absence of switching costs. In general, the two big operators tend to lose market share. After two years, AT&T and Verizon both lose about 7 percentage points in market shares. Market shares of the fringe and Sprint are basically unaffected. T-Mobile gains significantly: It's market share rises by 5 percentage points in the short-run and by 10 percentage points after two years. Reducing switching costs results in an increase of consumer surplus by 11% (net of the costs for the subsidy).

Table 2.14: Short-run price elasticities - subsidized switching costs

	Other	AT&T	Verizon	Sprint	T-Mobile
$p_{\text{AT\&T}}$	0.1134	-0.5061	0.2178	0.1842	0.2353
p_{Verizon}	0.0767	0.1981	-0.6005	0.2281	0.2696
p_{Sprint}	0.0359	0.1553	0.2101	-0.8626	0.1796
$p_{\text{T-Mobile}}$	0.1058	0.1862	0.2652	0.2426	-0.8896

Table 2.15: Medium-run price elasticities - subsidized switching costs

	Other	AT&T	Verizon	Sprint	T-Mobile
$p_{\text{AT\&T}}$	-0.0895	-1.4877	0.8077	-0.0051	0.0154
p_{Verizon}	0.2577	0.9741	-2.0429	0.5584	1.1600
p_{Sprint}	0.0430	-0.0759	0.7256	-1.3018	0.1646
$p_{\text{T-Mobile}}$	0.0112	0.2954	0.9994	0.4687	-1.6157

Table 2.16: Long-run price elasticities - subsidized switching costs

	Other	AT&T	Verizon	Sprint	T-Mobile
$p_{\text{AT\&T}}$	-0.2150	-1.8322	0.6480	-0.5042	0.9392
p_{Verizon}	-0.0587	0.3582	-4.1493	-0.4471	3.3838
p_{Sprint}	-0.0486	0.6997	0.5944	-1.6420	-0.0521
$p_{\text{T-Mobile}}$	0.2005	2.9865	0.2084	0.3025	-2.2231

Again, this counterfactual ignores possible reactions on the supply side. While one should be careful in interpreting the simulated industry structure, the results highlight once more the importance of consumer switching costs in the US wireless industry.

2.8 Conclusion

In this chapter, I developed an empirical framework to disentangle different sources of consumer inertia in the US wireless industry. The use of detailed group-level panel data allows me to identify preference heterogeneity from type-specific market shares and switching costs by matching the model's churn rate predictions to the observed counterparts. Identification of a localized network effect comes from comparing the dynamics of distinct local markets. The central condition for identification is that neither the characteristics defining consumer heterogeneity nor the characteristics defining reference groups are a weak subset of the other. The prime example of such a setting is looking at geographically separated markets with reference groups that consist of at least two types of heterogeneous consumers. If this condition is fulfilled, network effects can be estimated using a combination of the seminal framework by Berry, Levinsohn, and Pakes (1995) and dynamic panel techniques.

Even though the model was tailored towards the US wireless industry, my model is general enough to be applied to other industries where switching costs and network effects interact. In addition, my setup can be extended in several dimensions. First, in Chapter 3 I show how the framework can be generalized to a model in which consumers are forward-looking and have beliefs about the future industry evolution. Second, my model and my data are rich enough to be extended to a continuous-discrete choice model that allows for endogenous quantity choice in the style of Schiraldi, Seiler, and Smith (2011).

A framework that allows for separately identifying switching costs and network effects is not only necessary for obtaining correct estimates of price elasticities. Reliable demand side estimates are also essential when analyzing firms' pricing strategies in the spirit of Cabral (2011) and Chen (2014). In Chapter 4, I propose an empirical model of dynamic platform competition to endogenize carriers' pricing strategies. Supplementing my demand model with a full supply side model will allow for additional and much richer counterfactuals.

Estimation results from my demand model reveal that during my sample period (2006-2010) the market was characterized by the presence of both significant network effects and large switching costs. Switching costs range from US-$ 320 to US-$ 630. My estimates of network effects illustrate that on average consumers are willing to pay around US-$ 22 per month to be on one of the larger networks compared to a smaller one. I highlight the importance of being able to disentangle network effects and switching costs by comparing my results to models that ignore either one of the effects. When network effects are ignored, estimates of switching costs double. When switching costs are ignored, the magnitude of network effects increases by a factor of 10. To evaluate the importance of both effects further, I investigated the short- and long-run effects of reducing switching costs and of perfect network compatibility. The counterfactuals confirm that both switching costs and network effects are extremely important determinants of consumers' price elasticities and the market structure in the US wireless industry.

Appendix A Modeling network effects with additional data

If one has more detailed data on usage behavior and prices, one can allow consumers to buy different quantities of on-net and off-net minutes ($q^d_{jmt} = q^{d,\text{off}}_{jmt} + q^{d,\text{on}}_{jmt}$) at different prices p^{on}_{jt} and p^{off}_{jt}:

$$\delta^d_{jmt} = (X^d_{jmt}\beta^d + \gamma^d p^{\text{on}}_{jt} + \tilde{\alpha}^d s^{r_d}_{jmt} + \xi^d_{jmt})q^d_{jmt} + \gamma^d(p^{\text{off}}_{jt} - p^{\text{on}}_{jt})q^{d,\text{off}}_{jmt}$$

$\tilde{\alpha}$ should be interpreted as the pure network effect, that consumers get from simply being on a larger network net of the price effect on the monthly bill through a higher fraction of cheaper on-net minutes.

When on- and off-net quantities as well as on- and off-net prices are observed, one can re-write the total flow utility into a flow utility per service-unit:

$$\delta^d_{jmt} = (X^d_{jmt}\beta^d + \gamma^d p^{\text{on}}_{jt} + \tilde{\alpha}^d s^{r_d}_{jmt} + \xi^d_{jmt})q^d_{jmt} + \gamma^d(p^{\text{off}}_{jt} - p^{\text{on}}_{jt})q^{d,\text{off}}_{jmt} \tag{2.6}$$

$$\frac{\delta^d_{jmt}}{q^d_{jmt}} = (X^d_{jmt}\beta^d + \gamma^d p^{\text{on}}_{jt} + \tilde{\alpha}^d s^{r_d}_{jmt} + \xi^d_{jmt}) + \gamma^d(p^{\text{off}}_{jt} - p^{\text{on}}_{jt})(1 - f(s^{r_d}_{jmt})) \tag{2.7}$$

$$\tilde{\delta}^d_{jmt} = X^d_{jmt}\beta^d + \gamma^d p^{\text{off}}_{jt} + \tilde{\alpha}^d s^{r_d}_{jmt} - \gamma^d((p^{\text{off}}_{jt} - p^{\text{on}}_{jt}))f(s^{r_d}_{jt}) + \xi^d_{jmt} \tag{2.8}$$

$f(s^{r_d}_{jt}) = \frac{q^{d,\text{off}}_{jmt}}{q^d_{jmt}}$ denotes the ratio of off-net to total minutes and can be explicitly computed for any given calling pattern. In the most simple case of a random calling pattern, equation 2.8 simplifies to:

$$\tilde{\delta}^d_{jmt} = X^d_{jmt}\beta^d + \gamma^d p^{\text{off}}_{jt} + \underbrace{(\tilde{\alpha}^d - \gamma^d(p^{\text{off}}_{jt} - p^{\text{on}}_{jt}))}_{\alpha^d} s^{r_d}_{jmt} + \xi^d_{jmt} \tag{2.9}$$

Equation 2.9 is similar to the linear regression equation which I use after having backed-out the mean utilities δ and normalized for usage quantity. If detailed data on prices and quantities were available, one could take the more structural equation 2.8 to the data instead of the equation used in my estimation.

Appendix B Additional descriptive statistics

Table 2.17: Satisfaction measure and proxy for coverage quality

ctype	Statistic	satisfaction	qproxy
>45 years-poor	Mean	8.02	0.00
>45 years-rich	Mean	7.88	0.00
<45 years-poor	Mean	7.60	0.00
>45 years-rich	Mean	7.70	-0.00
>45 years-poor	SD	2.05	0.26
>45 years-rich	SD	1.90	0.24
<45 years-poor	SD	2.04	0.27
>45 years-rich	SD	1.89	0.25
>45 years-poor	Min	1.00	-0.88
>45 years-rich	Min	1.00	-0.88
<45 years-poor	Min	1.00	-0.87
>45 years-rich	Min	1.00	-0.88
>45 years-poor	Max	10.00	0.31
>45 years-rich	Max	10.00	0.35
<45 years-poor	Max	10.00	0.38
>45 years-rich	Max	10.00	0.38

Table 2.18: Number of survey respondents across markets

DMA	N
ATLANTA	12192
BALTIMORE	5962
BOSTON	14182
CHICAGO	19726
CLEVELAND	10154
DALLAS-FT. WORTH	15787
DETROIT	11425
LOS ANGELES	25006
MIAMI-FT. LAUDERDALE	6993
MINNEAPOLIS-ST. PAUL	10444
NEW YORK	38692
PHILADELPHIA	17981
PHOENIX	10990
PITTSBURGH	8153
SACRAMENTO-STOCKTON-MODESTO	6808
SALT LAKE CITY	5015
SAN FRANCISCO-OAKLAND-SAN JOSE	13009
SEATTLE-TACOMA	10753
TAMPA-ST. PETERSBURG	13010
WASHINGTON DC	9050

Appendix C Differences in price elasticities

Table 2.19: Differences in short-run price elasticities - perfect network compatibility

	Other	AT&T	Verizon	Sprint	T-Mobile
$p_{\text{AT\&T}}$	0.0637	0.0040	0.0182	0.0053	0.0015
p_{Verizon}	0.0434	0.0092	0.0026	0.0076	0.0049
p_{Sprint}	0.0511	0.0084	0.0191	0.0194	0.0032
$p_{\text{T-Mobile}}$	0.0934	0.0181	0.0290	0.0157	0.0273

Table 2.20: Differences in medium-run price elasticities - perfect network compatibility

	Other	AT&T	Verizon	Sprint	T-Mobile
$p_{\text{AT\&T}}$	0.0712	0.2594	-0.1039	-0.1115	-0.0739
p_{Verizon}	0.0659	-0.1306	0.1998	-0.1447	-0.1207
p_{Sprint}	0.0933	-0.0907	-0.0913	0.4153	-0.0512
$p_{\text{T-Mobile}}$	0.1467	-0.0276	-0.0286	-0.0244	0.4488

Table 2.21: Differences in long-run price elasticities - perfect network compatibility

	Other	AT&T	Verizon	Sprint	T-Mobile
$p_{\text{AT\&T}}$	0.0330	1.3469	-0.9105	-0.3318	-0.2734
p_{Verizon}	-0.0861	-1.0921	1.4496	-0.6807	-0.7233
p_{Sprint}	0.3169	-0.1668	-0.3954	1.3432	0.1728
$p_{\text{T-Mobile}}$	0.3640	-0.1531	-0.4723	0.1795	1.5300

Table 2.22: Differences in short-run price elasticities - subsidized switching costs

	Other	AT&T	Verizon	Sprint	T-Mobile
$p_{\text{AT\&T}}$	0.0064	-0.3382	0.1825	0.1256	0.1610
p_{Verizon}	-0.0286	0.1516	-0.4390	0.1750	0.1991
p_{Sprint}	-0.0768	0.0968	0.1678	-0.6142	0.0948
$p_{\text{T-Mobile}}$	0.0048	0.1418	0.2342	0.1875	-0.5750

Table 2.23: Differences in medium-run price elasticities - subsidized switching costs

	Other	AT&T	Verizon	Sprint	T-Mobile
$p_{\text{AT\&T}}$	-0.1803	-0.8047	0.5690	-0.2713	-0.2151
p_{Verizon}	0.1626	0.6982	-1.4286	0.2545	0.8824
p_{Sprint}	-0.0293	-0.3344	0.4793	-0.3467	-0.0691
$p_{\text{T-Mobile}}$	-0.0482	0.0848	0.8011	0.2467	-0.5621

Table 2.24: Differences in long-run price elasticities - subsidized switching costs

	Other	AT&T	Verizon	Sprint	T-Mobile
$p_{\text{AT\&T}}$	-0.3455	0.0846	-0.4666	-1.0458	0.4580
p_{Verizon}	-0.2949	-0.9485	-2.0585	-1.3439	2.4446
p_{Sprint}	0.0702	0.3048	-0.0308	0.4691	-0.1219
$p_{\text{T-Mobile}}$	0.2923	2.5309	-0.5657	0.1573	0.2475

Appendix D Market share graphs and tables

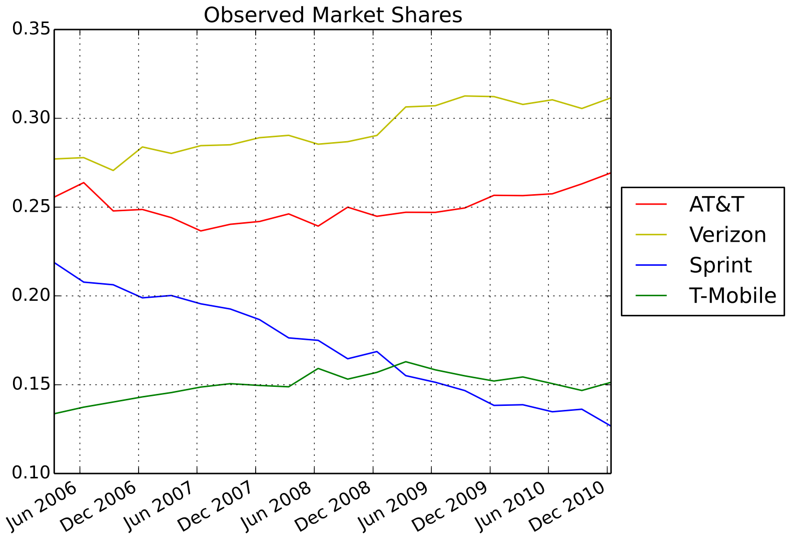
Table 2.25: Observed market shares

	Other	AT&T	Verizon	Sprint	T-Mobile
Q1-2006	0.1148	0.2556	0.2771	0.2188	0.1336
	0.1132	0.2638	0.2779	0.2078	0.1374
	0.1350	0.2479	0.2706	0.2063	0.1403
	0.1254	0.2487	0.2839	0.1989	0.1432
Q1-2007	0.1299	0.2441	0.2802	0.2002	0.1456
	0.1345	0.2366	0.2846	0.1956	0.1487
	0.1314	0.2403	0.2851	0.1926	0.1506
	0.1327	0.2419	0.2891	0.1867	0.1496
Q1-2008	0.1382	0.2462	0.2904	0.1764	0.1488
	0.1411	0.2393	0.2854	0.1750	0.1592
	0.1454	0.2500	0.2869	0.1646	0.1531
	0.1392	0.2448	0.2904	0.1687	0.1569
Q1-2009	0.1284	0.2471	0.3064	0.1551	0.1630
	0.1361	0.2470	0.3071	0.1514	0.1584
	0.1362	0.2495	0.3126	0.1467	0.1550
	0.1407	0.2567	0.3122	0.1384	0.1521
Q1-2010	0.1426	0.2565	0.3078	0.1387	0.1544
	0.1467	0.2575	0.3104	0.1348	0.1506
	0.1484	0.2631	0.3055	0.1362	0.1467
	0.1411	0.2693	0.3116	0.1267	0.1514

Table 2.26: Predicted market shares

	Other	AT&T	Verizon	Sprint	T-Mobile
Q1-2006	0.1144	0.2557	0.2773	0.2189	0.1337
	0.1136	0.2637	0.2777	0.2077	0.1373
	0.1348	0.2479	0.2707	0.2063	0.1403
	0.1264	0.2483	0.2835	0.1987	0.1430
Q1-2007	0.1299	0.2441	0.2802	0.2002	0.1456
	0.1347	0.2366	0.2845	0.1955	0.1487
	0.1318	0.2402	0.2850	0.1925	0.1505
	0.1325	0.2420	0.2892	0.1867	0.1496
Q1-2008	0.1376	0.2464	0.2906	0.1765	0.1489
	0.1408	0.2394	0.2855	0.1750	0.1592
	0.1458	0.2499	0.2866	0.1646	0.1531
	0.1391	0.2448	0.2904	0.1687	0.1569
Q1-2009	0.1286	0.2470	0.3064	0.1551	0.1629
	0.1359	0.2471	0.3072	0.1514	0.1584
	0.1359	0.2496	0.3128	0.1467	0.1550
	0.1409	0.2566	0.3121	0.1383	0.1520
Q1-2010	0.1432	0.2563	0.3076	0.1387	0.1543
	0.1466	0.2575	0.3105	0.1348	0.1506
	0.1484	0.2631	0.3055	0.1362	0.1467
	0.1411	0.2693	0.3115	0.1267	0.1513

Figure 2.6: Observed and predicted market shares



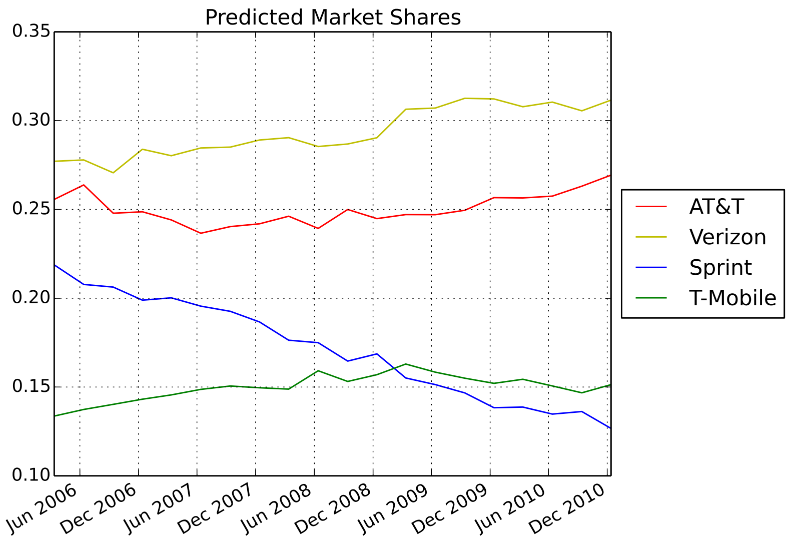


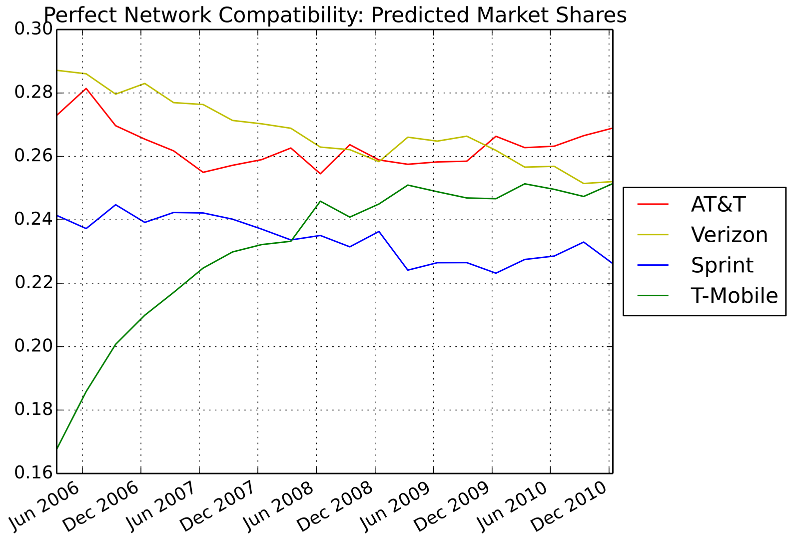
Table 2.27: Perfect network compatibility - predicted market shares

	Other	AT&T	Verizon	Sprint	T-Mobile
Q1-2006	0.0308	0.2729	0.2871	0.2414	0.1677
	0.0094	0.2814	0.2860	0.2372	0.1859
	0.0052	0.2697	0.2796	0.2448	0.2007
	0.0025	0.2654	0.2830	0.2392	0.2099
Q1-2007	0.0019	0.2617	0.2769	0.2423	0.2171
	0.0017	0.2550	0.2764	0.2422	0.2248
	0.0014	0.2572	0.2713	0.2402	0.2299
	0.0015	0.2590	0.2703	0.2371	0.2322
Q1-2008	0.0016	0.2626	0.2689	0.2336	0.2332
	0.0016	0.2545	0.2629	0.2351	0.2459
	0.0019	0.2637	0.2621	0.2315	0.2408
	0.0015	0.2589	0.2583	0.2363	0.2450
Q1-2009	0.0014	0.2575	0.2660	0.2241	0.2509
	0.0016	0.2583	0.2648	0.2265	0.2489
	0.0018	0.2585	0.2664	0.2265	0.2469
	0.0019	0.2663	0.2619	0.2232	0.2467
Q1-2010	0.0018	0.2628	0.2566	0.2275	0.2514
	0.0017	0.2632	0.2569	0.2286	0.2496
	0.0017	0.2665	0.2515	0.2330	0.2474
	0.0014	0.2689	0.2521	0.2262	0.2514

Table 2.28: Perfect network compatibility - predicted differences in market shares

	Other	AT&T	Verizon	Sprint	T-Mobile
Q1-2006	-0.0840	0.0173	0.0100	0.0226	0.0340
	-0.1038	0.0176	0.0082	0.0295	0.0485
	-0.1298	0.0218	0.0090	0.0385	0.0605
	-0.1229	0.0168	-0.0009	0.0403	0.0668
Q1-2007	-0.1280	0.0176	-0.0033	0.0421	0.0715
	-0.1328	0.0184	-0.0083	0.0466	0.0761
	-0.1299	0.0168	-0.0138	0.0476	0.0793
	-0.1312	0.0171	-0.0188	0.0504	0.0826
Q1-2008	-0.1366	0.0165	-0.0216	0.0573	0.0844
	-0.1395	0.0152	-0.0225	0.0601	0.0867
	-0.1436	0.0137	-0.0247	0.0669	0.0877
	-0.1377	0.0140	-0.0320	0.0676	0.0880
Q1-2009	-0.1271	0.0104	-0.0404	0.0690	0.0880
	-0.1345	0.0112	-0.0423	0.0751	0.0905
	-0.1344	0.0089	-0.0462	0.0798	0.0919
	-0.1387	0.0097	-0.0503	0.0848	0.0946
Q1-2010	-0.1408	0.0063	-0.0512	0.0888	0.0970
	-0.1449	0.0057	-0.0536	0.0938	0.0990
	-0.1467	0.0034	-0.0541	0.0968	0.1006
	-0.1397	-0.0004	-0.0595	0.0995	0.1001

Figure 2.7: Perfect network compatibility: market shares



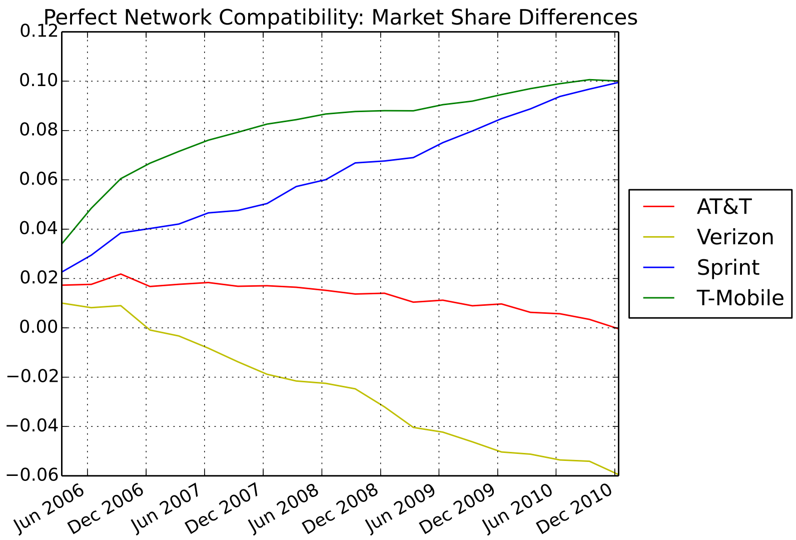


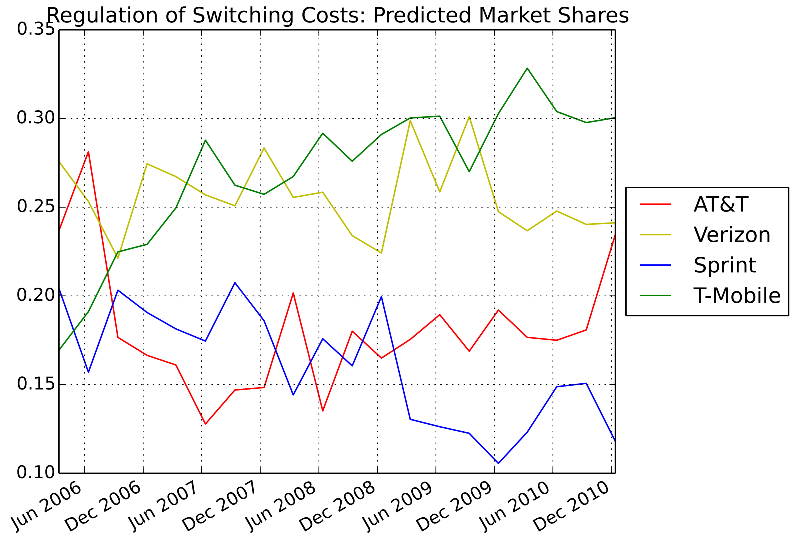
Table 2.29: Regulation of switching costs - predicted market shares

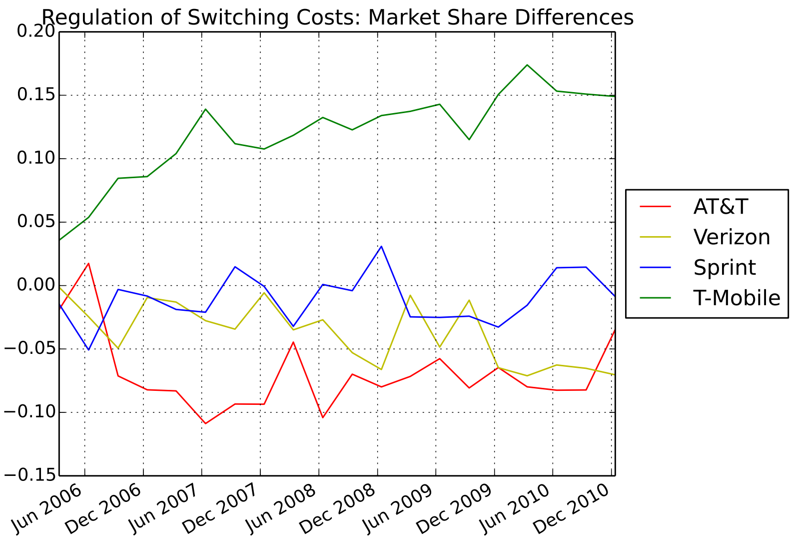
	Other	AT&T	Verizon	Sprint	T-Mobile
Q1-2006	0.1139	0.2367	0.2757	0.2042	0.1694
	0.1174	0.2813	0.2532	0.1570	0.1911
	0.1741	0.1766	0.2213	0.2032	0.2248
	0.1394	0.1665	0.2744	0.1906	0.2291
Q1-2007	0.1407	0.1610	0.2672	0.1814	0.2496
	0.1530	0.1278	0.2569	0.1745	0.2877
	0.1325	0.1470	0.2508	0.2074	0.2624
	0.1250	0.1484	0.2834	0.1860	0.2572
Q1-2008	0.1314	0.2016	0.2555	0.1442	0.2673
	0.1388	0.1352	0.2584	0.1758	0.2917
	0.1495	0.1801	0.2340	0.1606	0.2759
	0.1203	0.1650	0.2242	0.1996	0.2910
Q1-2009	0.0951	0.1755	0.2988	0.1304	0.3003
	0.1244	0.1894	0.2586	0.1263	0.3013
	0.1376	0.1688	0.3011	0.1226	0.2700
	0.1522	0.1920	0.2475	0.1056	0.3027
Q1-2010	0.1351	0.1766	0.2367	0.1232	0.3283
	0.1245	0.1750	0.2478	0.1488	0.3039
	0.1305	0.1808	0.2403	0.1507	0.2977
	0.1057	0.2347	0.2412	0.1179	0.3004

Table 2.30: Regulation of switching costs - predicted differences in market shares

	Other	AT&T	Verizon	Sprint	T-Mobile
Q1-2006	-0.0009	-0.0189	-0.0014	-0.0146	0.0358
	0.0042	0.0175	-0.0247	-0.0508	0.0538
	0.0391	-0.0712	-0.0494	-0.0031	0.0846
	0.0140	-0.0822	-0.0095	-0.0083	0.0859
Q1-2007	0.0109	-0.0831	-0.0130	-0.0188	0.1040
	0.0184	-0.1088	-0.0277	-0.0210	0.1391
	0.0011	-0.0934	-0.0343	0.0148	0.1118
	-0.0077	-0.0935	-0.0057	-0.0007	0.1077
Q1-2008	-0.0068	-0.0446	-0.0349	-0.0322	0.1184
	-0.0022	-0.1041	-0.0270	0.0009	0.1325
	0.0041	-0.0699	-0.0529	-0.0040	0.1228
	-0.0189	-0.0799	-0.0662	0.0309	0.1340
Q1-2009	-0.0334	-0.0716	-0.0077	-0.0247	0.1373
	-0.0117	-0.0576	-0.0485	-0.0251	0.1429
	0.0013	-0.0807	-0.0115	-0.0241	0.1150
	0.0115	-0.0646	-0.0648	-0.0328	0.1507
Q1-2010	-0.0075	-0.0799	-0.0711	-0.0155	0.1740
	-0.0222	-0.0825	-0.0626	0.0140	0.1533
	-0.0179	-0.0823	-0.0652	0.0145	0.1509
	-0.0353	-0.0346	-0.0704	-0.0087	0.1491

Figure 2.8: Regulation of switching costs: market shares





Appendix E Empirical evidence on contract structures and calling patterns

Figure 2.9 and 2.11 display information on postpaid cellphone contracts in the US at various years during and shortly after my sample period (2006, 2008 and 2011). This information was crawled from the Internet by using the Internet Archive-Waybackmachine (`http://web.archive.org`). The term *mobile-to-mobile minutes* denotes the minutes available for making and receiving calls from people with the same provider. Although not every contract offers unlimited mobile-to-mobile minutes, many operators do have at least some contract with on-net discounts in some form throughout my sample period and beyond. My survey data does not contain explicit information on the number of consumers that are subscribed to contracts with free mobile-to-mobile minutes. In order to get an idea on these numbers, I obtain information on the characteristics of the most common contracts from Internet archives. A lower bound for the number of people who have on-net discounts in their contract would be those who pay less for their plan that the costs of the most basic unlimited-minutes plan. At the beginning of my sample period these unlimited plans started at around US-$ 70-80 while at the end of the sample period these contracts were already available for around US-$ 50.[11] Based on these numbers, I conjecture that at the beginning of my sample period, at least 75% of consumers had contracts with on-net discounts in some form, while at the end of my sample, still more than 50% should have had contracts with on-net discounts. This supports the claim that tariff-mediated network effects have played a role in the US wireless market during my sample period.

[11]Source: http://www.costhelper.com/cost/electronics/cell-phone-plans.html

Figure 2.9: Information on wireless contracts from 2006

2006 CELL PHONE PROVIDERS REPORT

eMAIL TO A FRIEND

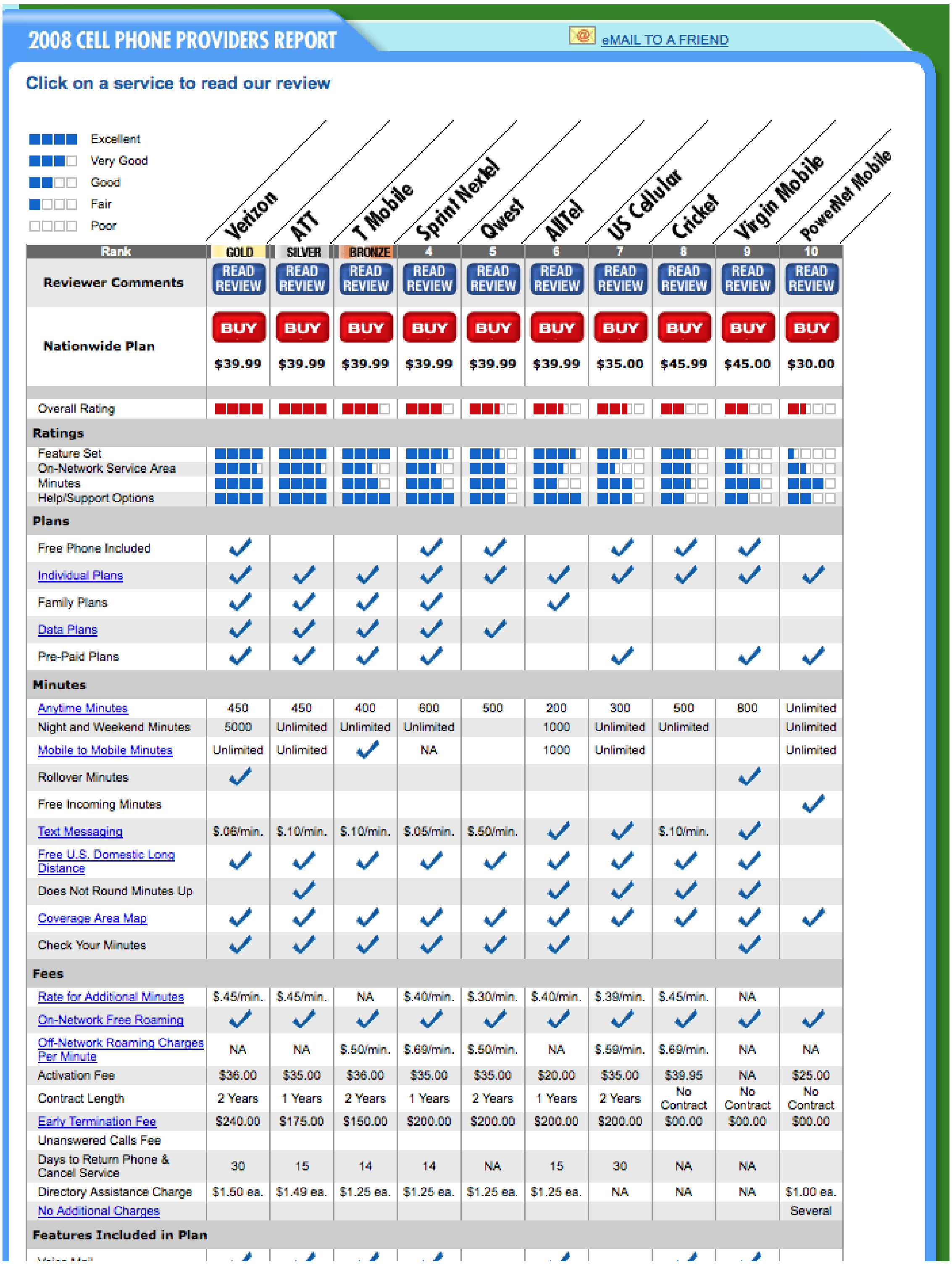
Click on a product name to read our review

■■■■ Excellent
■■■□ Very Good
■■□□ Good
■□□□ Fair
□□□□ Poor

	Cingular	Verizon	Sprint - Nextel	T-Mobile	Qwest	Alltel	Cellular One	PowerNet Mobile	Liberty Wireless	Cricket
Rank	GOLD	SILVER	BRONZE	4	5	6	7	8	9	10
Reviewer Comments	READ REVIEW	READ REVIEW	READ REVIEW	READ REVIEW	READ REVIEW	READ REVIEW	READ REVIEW	READ REVIEW	READ REVIEW	READ REVIEW
Nationwide Plan	BUY $39.99	BUY $39.99	BUY $34.99	BUY $39.99	BUY $39.99	BUY $39.99	BUY $35.00	BUY $37.99	BUY $44.99	BUY $30.00
Overall Rating	■■■■	■■■■	■■■□	■■■□	■■◧□	■■◧□	■■◧□	■■□□	■■□□	■◧□□
Ratings										
Feature Set	■■■■	■■■■	■■■■	■■■◧	■■◧□	■■■◧	■■◧□	■■◧□	■◧□□	◧□□□
On-Network Service Area	■■■◧	■■■◧	■■◧□	■■◧□	■■■□	■■◧□	■◧□□	■■◧□	■◧□□	■◧□□
Minutes	■■■■	■■■■	■■■□	■■■□	■■■□	■■□□	■■■□	■■◧□	■■■□	■■■□
Help/Support Options	■■■■	■■■■	■■■■	■■■■	■■■□	■■■■	■■■□	■■□□	■■□□	■■□□
Plans										
Free Phone Included	✓			✓	✓		✓	✓	✓	
Individual Plans	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Family Plans	✓	✓	✓	✓		✓				
Data Plans	✓	✓	✓	✓	✓					
Pre-Paid Plans	✓	✓	✓	✓			✓		✓	✓
Minutes										
Anytime Minutes	450	450	400	600	500	200	300	500	800	Unlimited
Night and Weekend Minutes	5000	Unlimited	Unlimited	Unlimited		1000	Unlimited	Unlimited		Unlimited
Mobile to Mobile Minutes	Unlimited	Unlimited	✓	NA		1000	Unlimited			Unlimited
Rollover Minutes	✓								✓	
Free Incoming Minutes										✓
Text Messaging	$.06/min.	$.10/min.	$.10/min.	$.05/min.	$.50/min.	✓	✓	$.10/min.	✓	
Free U.S. Domestic Long Distance	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Does Not Round Minutes Up		✓				✓	✓	✓	✓	
Coverage Area Map	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Check Your Minutes	✓	✓	✓	✓	✓	✓			✓	
Fees										
Rate for Additional Minutes	$.45/min.	$.45/min.	NA	$.40/min.	$.30/min.	$.40/min.	$.39/min.	$.45/min.	NA	
On-Network Free Roaming	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Off-Network Roaming Charges Per Minute	NA	NA	$.50/min.	$.69/min.	$.50/min.	NA	$.59/min.	$.69/min.	NA	NA
Activation Fee	$36.00	$35.00	$36.00	$35.00	$35.00	$20.00	$35.00	$39.95	NA	$25.00
Contract Length	2 Years	1 Years	2 Years	1 Years	2 Years	1 Years	2 Years	No Contract	No Contract	No Contract
Early Termination Fee	$240.00	$175.00	$150.00	$200.00	$200.00	$200.00	$200.00	$00.00	$00.00	$00.00
Unanswered Calls Fee										
Days to Return Phone & Cancel Service	30	15	14	14	NA	15	30	NA	NA	

Source: `http://cell-phone-providers-review.toptenreviews.com`

Figure 2.10: Information on wireless contracts from 2008



2008 CELL PHONE PROVIDERS REPORT

eMAIL TO A FRIEND

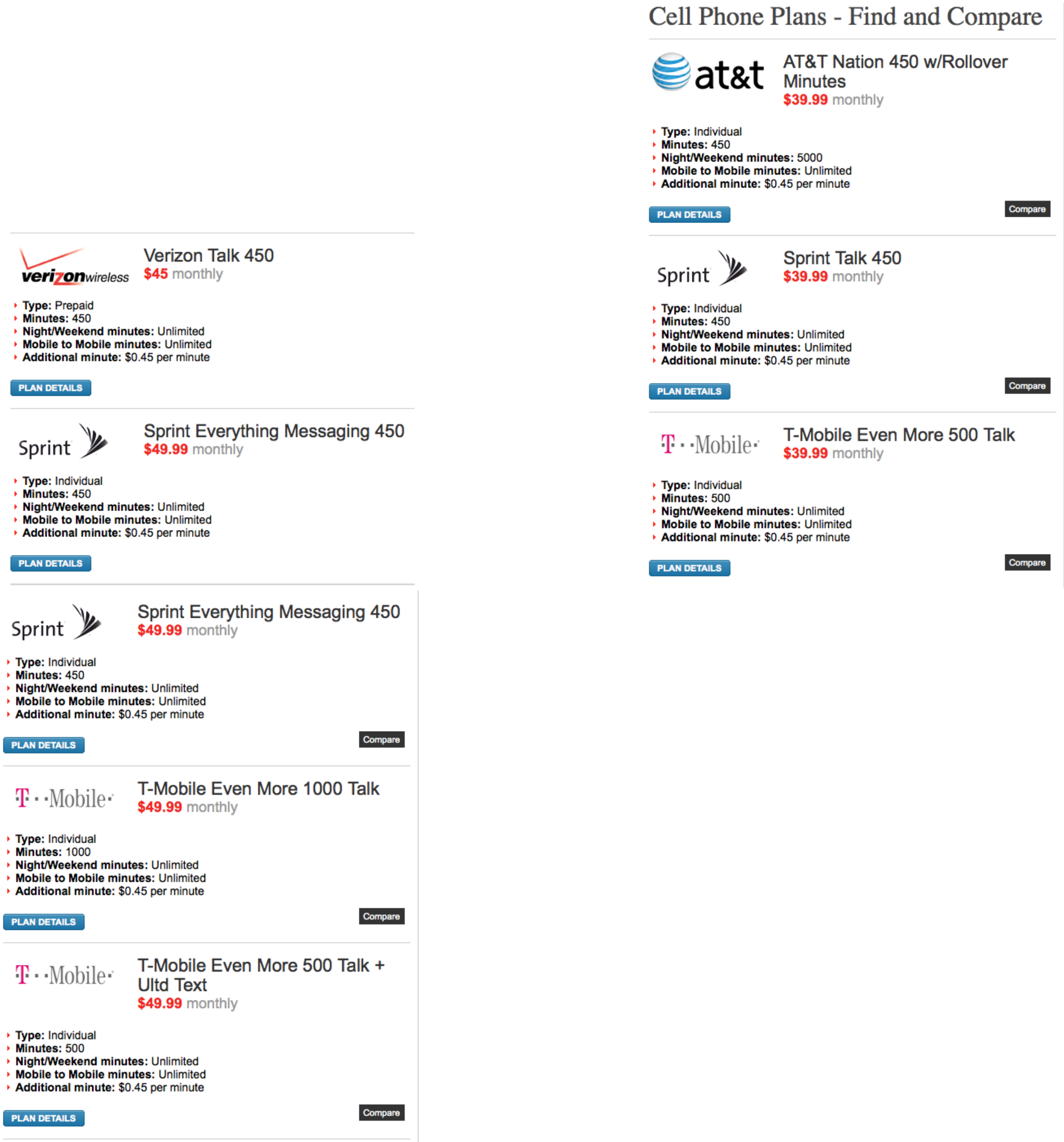
Click on a service to read our review

Excellent
Very Good
Good
Fair
Poor

	Verizon	ATT	T Mobile	Sprint Nextel	Qwest	AllTel	US Cellular	Cricket	Virgin Mobile	PowerNet Mobile
Rank	GOLD	SILVER	BRONZE	4	5	6	7	8	9	10
Reviewer Comments	READ REVIEW	READ REVIEW	READ REVIEW	READ REVIEW	READ REVIEW	READ REVIEW	READ REVIEW	READ REVIEW	READ REVIEW	READ REVIEW
Nationwide Plan	BUY $39.99	BUY $39.99	BUY $39.99	BUY $39.99	BUY $39.99	BUY $39.99	BUY $35.00	BUY $45.99	BUY $45.00	BUY $30.00
Overall Rating										
Ratings										
Feature Set										
On-Network Service Area										
Minutes										
Help/Support Options										
Plans										
Free Phone Included	✓			✓	✓		✓	✓	✓	
Individual Plans	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Family Plans	✓	✓	✓	✓		✓				
Data Plans	✓	✓	✓	✓	✓					
Pre-Paid Plans	✓	✓	✓	✓			✓		✓	✓
Minutes										
Anytime Minutes	450	450	400	600	500	200	300	500	800	Unlimited
Night and Weekend Minutes	5000	Unlimited	Unlimited	Unlimited		1000	Unlimited	Unlimited		Unlimited
Mobile to Mobile Minutes	Unlimited	Unlimited	✓	NA		1000	Unlimited			Unlimited
Rollover Minutes	✓								✓	
Free Incoming Minutes										✓
Text Messaging	$.06/min.	$.10/min.	$.10/min.	$.05/min.	$.50/min.	✓	✓	$.10/min.	✓	
Free U.S. Domestic Long Distance	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Does Not Round Minutes Up		✓				✓	✓	✓	✓	
Coverage Area Map	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Check Your Minutes	✓	✓	✓	✓	✓	✓			✓	
Fees										
Rate for Additional Minutes	$.45/min.	$.45/min.	NA	$.40/min.	$.30/min.	$.40/min.	$.39/min.	$.45/min.	NA	
On-Network Free Roaming	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Off-Network Roaming Charges Per Minute	NA	NA	$.50/min.	$.69/min.	$.50/min.	NA	$.59/min.	$.69/min.	NA	NA
Activation Fee	$36.00	$35.00	$36.00	$35.00	$35.00	$20.00	$35.00	$39.95	NA	$25.00
Contract Length	2 Years	1 Years	2 Years	1 Years	2 Years	1 Years	2 Years	No Contract	No Contract	No Contract
Early Termination Fee	$240.00	$175.00	$150.00	$200.00	$200.00	$200.00	$200.00	$00.00	$00.00	$00.00
Unanswered Calls Fee										
Days to Return Phone & Cancel Service	30	15	14	14	NA	15	30	NA	NA	
Directory Assistance Charge	$1.50 ea.	$1.49 ea.	$1.25 ea.	$1.25 ea.	$1.25 ea.	$1.25 ea.	NA	NA	NA	$1.00 ea.
No Additional Charges										Several
Features Included in Plan										
Voice Mail	✓	✓	✓	✓		✓		✓	✓	

Source: `http://cell-phone-providers-review.toptenreviews.com`

Figure 2.11: Information on wireless contracts from 2011



Source: `http://www.phonearena.com`

3 Quantifying Network Effects and Switching Costs in Dynamic Demand Models

3.1 Introduction

In this chapter, I extend the framework proposed in Chapter 2 to a model of forward-looking consumers. In most high-tech consumer goods industries, it is very plausible to assume that consumers are at least partially forward-looking. In the wireless industry, carriers continuously introduce new service features and expand their coverage quality while consumers are usually locked-in into a contract for 24 months. When individuals are aware that contemporaneous decisions affect future payoffs, they should take into account their expectations on the future.

For example, consumers may choose to subscribe to a low-quality product today if they expect it to become sufficiently better in the future. Analyzing this aspect requires a model of forward-looking consumers who not only consider instantaneous payoffs, but maximize a discounted lifetime utility given their beliefs about the future industry state.

A dynamic and a myopic model can be considered as equivalent when consumers are forward-looking, but have static expectations. In this case, running counterfactuals with the myopic model should yield correct results. However, the interpretation of the estimates is not clear in such a model. The myopic utility function contains both flow pay-off components, such as utility from coverage quality or network effects, and the one-time utility component of the switching cost. Meaningfully comparing for example the relative magnitude of switching costs and network effects becomes impossible. To tackle these problems, I incorporate direct network effects into a dynamic demand model in the style of Gowrisankaran and Rysman (2012).

A dynamic model is much more involved both in terms of identification arguments and the estimation. I discuss the additional assumptions under which the identification strategy from Chapter 2 can be extended to a dynamic model. In essence, my identification strategy for the network effect requires that the sequentially exogenous instruments for reference group market shares are not a direct state variable in consumers' value functions. In a model without unobserved preference heterogeneity in which all state variables evolve according to an $AR(1)$-process, the identifying assumptions are satisfied.

Ex-ante, it is not clear how the estimates from a myopic model will compare to the ones obtained from estimating a dynamic model. In my application to the US wireless industry, the results from the dynamic model are qualitatively in line with the ones in Chapter 2. Although estimates for both switching costs and network effects are large and significant, they are generally 30%-50% lower than the ones obtained from a myopic model. When evaluating the demand side effects of perfect network compatibility or a reduction in switching costs, the smaller carriers generally gain market share. However, in comparison to the myopic model, forward-looking consumers react less strongly but much faster.

In Section 3.2, I present the dynamic extension of the demand model developed in Chapter 2. I discuss the assumptions necessary to identify network effects in Section 3.4. Section 3.5 outlines the estimation algorithm. The following two sections discuss the estimation results and the counterfactual outcomes when regulating switching costs or network effects. Section 3.8 concludes.

3.2 Model

In this section, I present a dynamic discrete-choice model in which consumer decisions are driven by both switching costs and network effects. The framework extends the recent literature on dynamic demand models by incorporating direct network effects. The model is tailored to capture key aspects of the US wireless industry, although it is generally applicable to a broad range of network industries.

3.2.1 Static components

As in Chapter 2, the per-period utility function is given by:

$$u^i_{jmt} = \underbrace{(X^d_{jmt}\beta^d + \gamma^d p^d_{jmt} + \xi^d_{jmt} + \alpha^d s^{r_d}_{jmt})q^d_{jmt}}_{\delta^d_{jmt}} + \psi^d \mathbb{1}_{\{a^i_{t-1} \neq a^i_t\}} + \epsilon^i_{jmt}$$

where i indexes an individual consumer, d denotes a (demographic) consumer type, m the local market, t the time period and a^i_{t-1} consumer i's choice in period $t-1$. Following the notation in Chapter 2, X denotes observable product characteristics, p the quarterly subscription price, ξ an unobservable (to the econometrician) vertical product characteristic, s^{r_d} the market share within a consumer's reference group and q the (exogenously given) usage quantity.

3.2.2 Model of forward-looking consumers

The dynamic extension of my model is based on a recent series of papers on dynamic demand (Gowrisankaran and Rysman 2012; Shcherbakov 2013; Nosal 2012; Conlon 2011). Consumer i's infinite-horizon decision problem can be described by a value function:

$$\begin{aligned} V^i(\tilde{j}, \epsilon_{it}, \Omega_t) = \max\{&\delta^i_{\tilde{j}t} + \epsilon_{i\tilde{j}t} + \beta E[V^i(\tilde{j}, \Omega_{t+1})|\Omega_t)], \\ &\max_{j \neq \tilde{j}}\{-\psi^i + \delta^i_{jt} + \epsilon_{ijt} + \beta E[V^i(j, \Omega_{t+1})|\Omega_t]\}\} \end{aligned}$$

with β denoting the discount factor and $\tilde{j}$ the product owned at the beginning of the period. A consumer can be subscribed to exactly one wireless carrier. If she subscribes to a new operator, the old contract is canceled at a cost included in the switching cost ψ^i. Ω denotes the industry state which contains all payoff-relevant information. So the relevant state space of a consumer is characterized by $(\tilde{j}, \epsilon_{it}, \Omega_t)$. Product characteristics such as coverage quality, call rates and network size may change every period. Therefore $\delta^i_{\tilde{j}t}$ is not fixed to be the same as in the initial purchase period in contrast to the models by Gowrisankaran and Rysman (2012) or Conlon (2011).

I assume that the industry characteristics Ω evolve according to an exogenous Markov process $g(\Omega_{t+1}|\Omega_t)$. This implies assuming that from the perspective of an individual consumer, also the evolution of reference group market shares are exogenous. This can be justified if an individual consumer does not have a substantial effect on the market share distribution. This is the case if each (disaggregated) market share observation is generated by a continuum of consumers.

Because of the logit error structure the ex-ante value function of owning product $\tilde{j}$ at the beginning of period t can be written in closed-form as:

$$\mathbb{E}(V^i(\tilde{j},\Omega_t)) = v^i(\tilde{j},\Omega) = \log[\exp(\delta^i_{\tilde{j}} + \beta E[V^i(\tilde{j},\Omega')|\Omega]) + \exp(\Delta^i(\tilde{j},\Omega))]$$

which is obtained by integrating over the *iid* shock ϵ. The *inclusive value* Δ^i captures the present discounted value of choosing the best alternative today except for the one currently owned and can be written as:

$$\Delta^i(\tilde{j},\Omega) = \log\left(\sum_{j\neq\tilde{j}} \exp(\delta^i_j - \psi^i + \beta E[V^i(j,\Omega')|\Omega])\right)$$

In order to compute consumers' beliefs one needs to specify how they perceive the transition of the state variables. In fast-moving high-tech industries it is very unlikely that consumers have perfect foresight on the industry structure. Therefore, most of the literature models state transitions in a bounded rationality framework. Consumers' predictions of future state variables are a simple function of contemporaneous state variables, such as product characteristics, prices, switching costs and market shares. The coefficients of the transition functions are estimated in auxiliary regressions imposing that individuals are correct on average. Such a specification need not be consistent with an economic model of the supply side, but it is computationally tractable.

I follow the literature in applying a bounded rationality approach. I assume that observed operator characteristics evolve according to an $AR(1)$-process. Also, the unobserved product characteristic ξ follows a (stable) $AR(1)$-process with a mean-zero innovation ν implying that $\mathbb{E}(\xi_{t+1}) = \iota\xi_t$ with $\iota < 1$.

An additional complication in my model is that consumers need not only forecast exogenous product characteristics but also future market shares. Once consumers know Ω_t, market shares in period $t+1$ are not stochastic anymore. Instead they can be computed as the fixed point of a mapping from the industry structure and beliefs on reference group market shares to market shares:

$$\begin{aligned} s^{r_d}_{jmt+1} &= \sum_{d' \in r_d} w^{d'}_{mt} \mathbb{E} s^{d'}_{jmt+1} \\ &= \sum_{d' \in r_d} w^{d'}_{mt} \sum_{j'} Pr^{d'}(j|j') s^{d'}_{jmt} \end{aligned}$$

Fully modeling this aspect is problematic because the presence of multiple equilibria can lead to multiple fixed points. With forward-looking consumers this is a more complicated issue than in the myopic case. The estimation of such a dynamic model would require finding all the solutions of the value function and then selecting one equilibrium which makes the model substantially more complicated and harder to compute (cf. Section 3.5). To circumvent this problem, I assume that consumers forecast market shares in the same boundedly rational way as the exogenous product characteristics. This results in a unique equilibrium prediction and is therefore much easier to compute. Tackling the issue of multiple equilibria with a more sophisticated belief structure is left for future research.

A dynamic model in which consumers keep track of each state variable individually is computationally infeasible. Usually, the literature adopts an *inclusive value sufficiency* assumption that allows consumers to track only the mean utility of their current product as well as a summary statistic of the market. In general, the inclusive value assumption is restrictive as two industry states with very different future paths can result in the same inclusive value. In industries where the choice set consists of many different products, the IVS assumption is indispensable.

In my model, there are just 4 inside goods. At a significant but manageable increase in computational complexity, it should be possible to replace the IVS assumption by the weaker assumption that consumers track the mean utilities of all products. I leave the estimation of this model for future research. For this chapter, I follow Gowrisankaran and Rysman (2012) in imposing the logit inclusive value sufficiency assumption:

$$\begin{aligned} \Delta^i(\Omega) &= \Delta^i(\hat{\Omega}) \\ \Rightarrow g_\Delta(\Delta(\Omega')|\Omega) &= g_\Delta(\Delta(\hat{\Omega}'|\hat{\Omega})) \end{aligned}$$

For the evolution of the flow utility of the good currently owned, the LIV assumption implies:

$$\begin{aligned} \delta^i_j(\Omega) &= \delta^i_j(\hat{\Omega}) \\ \Rightarrow g_\delta(\delta^i(j,\Omega')|\Omega) &= g_\delta(\delta(j,\hat{\Omega}'|\hat{\Omega})) \end{aligned}$$

While it is rather unlikely that the industry actually evolves in such a way, this specification can be interpreted as consumers being able only to track a summary statistic of the overall market and the evolution of their own product (Gowrisankaran and Rysman 2012). This is a plausible behavioral assumption in highly dynamic industries such as the wireless industry.

The evolution of the summary statistics are modeled as two stationary $AR(1)$-processes:

$$\begin{aligned} \Delta_{t+1} &= \gamma_1 + \gamma_2 \Delta_t + \nu_{\Delta t+1} \\ \delta_{jt+1} &= \tau_0 + \tau_1 \delta_{jt} + \nu_{\delta t+1} \end{aligned}$$

where γ and τ are nuisance parameters to be estimated in auxiliary OLS-regressions. In order to compute the model's market share predictions, define the utility of consumer i when choosing product j in period t net of any switching costs as:

$$w^i_{jt} = \delta^i_{jt} + \beta \mathbb{E}(V^i(j,\Omega_{t+1})|\Omega_t)$$

With i's previous period's choice given by $\tilde{j}$, the conditional choice probabilities can be written as:

$$\begin{aligned} Pr^i_t(\tilde{j}|\tilde{j}) &= \frac{\exp(w^i_{\tilde{j}t})}{\exp(w^i_{\tilde{j}t}) + \exp(\Delta^i(\tilde{j},\Omega))} \\ Pr^i_t(j|\tilde{j}) &= \frac{\exp(w^i_{jt} - \psi^i)}{\exp(w^i_{jt} - \psi^i) + \exp(\Delta^i(j,\Omega))} \end{aligned}$$

Consequently, market share and churn rate predictions can be computed recursively:

$$
\begin{aligned}
s^i_{jt} &= \sum_{j'} Pr^i_t(j|j')s^i_{j't-1} \\
c^i_{jt} &= 1 - Pr^i_t(j|j)
\end{aligned}
$$

These model predictions can be taken to the data to form moment conditions.

3.3 Data requirements

The estimation of the dynamic model is based on the same data that is used in Chapter 2 to estimate the model with myopic consumers.

3.4 Identification arguments

In the previous chapter, I focused on the identification arguments for a model with myopic consumers. In the following, I discuss the additional assumptions under which my identification strategy can be generalized to a model with forward-looking consumers.

In the myopic model, I used the lagged market shares of other consumer types in i's reference group as instruments for the contemporaneous reference group market share of consumer type i. With forward-looking consumers, additional identification issues arise. The key problem with a dynamic model is that the sequentially exogenous instruments used to identify the network effect are excluded from the instantaneous flow utility, but they may be state variables in the value function. In this case, the value functions would be a direct function of the instruments used to identify the network effect. As the value functions are required to back out the structural demand error ξ, the instruments could shift a consumer's utility not only through the network effect, but also directly through the value function. Consequently, the exclusion restrictions discussed in the myopic model may be violated if the state space of the value function is unrestricted. Therefore, I make the following assumption on the state space of consumers' value functions.

Assumption 3.4.1. *The instruments Z used for reference group market shares are not explicit state variables in the value functions. In addition, consumers forecast the evolution of the state variables only based on the most recent value of the state variables. In particular, information contained in the instruments for reference group market shares are not used to forecast future state variables.*

$$\begin{aligned} V_j(\{\delta_j, \Delta_j)\}_{j=1}^J, Z) &= \delta_j + \beta \int V(\{\delta'_j, \Delta'_j)\}_{j=1}^J, Z') f(\{\delta'_j, \Delta'_j)\}_{j=1}^J, Z' | \delta, \Delta, Z) \\ &= \delta_j + \beta \int V(\{\delta'_j, \Delta'_j)\}_{j=1}^J) f(\{\delta'_j, \Delta'_j)\}_{j=1}^J | \delta, \Delta) \end{aligned}$$

Assumption 3.4.1 is implied by the assumption that consumers have homogeneous preferences within a consumer type and the assumption that all state variables evolve according to an $AR(1)$-process. This implies that the current state is a sufficient statistic for the past so that state realizations from period $t-1$ do not provide additional information to forecast the future.

Under Assumption 3.4.1, the algorithm backing out ξ_{t+1}^d from s_{t+1}^d, s_{t+1}^{-d}, s_t^d and $V^d(\Omega_{t+1})$ will not depend directly on s_{t-1}^{-d}. Together with the sequential exogeneity assumption on ν, this implies that the moment conditions used for the myopic model are also valid in a dynamic model with forward-looking consumers.

In general, the assumptions made to reduce the state space in dynamic demand models are made purely for computational reasons. Admittedly, they have a more restrictive role in my application. They are required not only to implement the estimation, but also as part of the identification arguments. I require some form of boundedly rational consumers to identify the network effect. For high-tech consumer goods industries, this assumption may not be a bad one. Given the fast evolution of these industries, consumers may quickly forget about previous periods' industry state and only base their decision on the most recent realization of the state variables. If one has strictly, not just sequentially, exogenous instruments, one could relax this assumption. For example, if one had exogenous quality characteristics that affect only a subset of consumer types within a reference group and not others, these characteristics would be much better instruments for carriers' network size. Unfortunately these instruments are hard to come up with in my application.

Additional identification issues in dynamic models As the discount factor is generally not identified, I set it to $\beta = 0.975$ which is equivalent to a yearly discount factor of 0.9. The identification of dynamic demand in general is a very important but still open issue in the literature. In a dynamic model with forward-looking consumers not all products (across firms and time) are substitutes. Therefore, it is not possible to extend the classical proof of a unique fixed point by Berry, Levinsohn, and Pakes (1995), cf. Gowrisankaran and Rysman (2012). I follow the literature in imposing the assumption that this system has a unique fixed point and check empirically that different starting values always result in the same solution. Formally proving the uniqueness of the fixed point of the dynamic system is a challenging but extremely important topic for future research.

3.5 Estimation algorithm

The dynamic model can be estimated using either a nested fixed-point (NFXP) algorithm or the more efficient MPEC approach (see Appendix A). For the estimation in this chapter, I adopt the NFXP routine as used by Gowrisankaran and Rysman (2012) and Nosal (2012). The estimation algorithm consists of three levels:

Inner loop The inner loop takes a guess for the parameters θ and a level of per-period flow utilities δ as given. These are used to solve the dynamic programming problem resulting in updated guesses for the predicted choice probabilities. Technically, this step involves finding a joint fixed point of the following set of equations:

1. Value functions / Bellman equations (for each consumer type i)
2. Logit inclusive values: $\Delta^i(j, \Omega)$ for every market share observation
3. $AR(1)$-regressions for the evolution of Δ^i and δ^i (for each consumer type i)

For solving the value functions, one needs to discretize the state space for (δ, Δ) and take meaningful starting guesses for the value functions, the inclusive values Δ and the $AR(1)$-regression coefficients. In practice, I discretize each state variable into 50 grid points. I solve the value function on this 50×50 grid and use linear interpolation to compute the values between the grid points. The bounds of the grid are chosen such that the inner loop never hits the boundaries.

The initial guesses for the value functions and the inclusive values are based on a model with static expectations. For the value function, I set it to the contemporaneous flow utility normalized with $\frac{1}{1-\beta}$. Initial values for the inclusive values are calculated based on these value functions.

In order to compute the continuation values, one needs to simulate the evolution of both state variables. For each grid point, I draw $ns = 80$ shocks for each state variable and compute the value function at the simulated states. The continuation value is calculated as the average over the ns simulated outcomes.

Middle loop The middle loop executes the inversion step similarly to Berry, Levinsohn, and Pakes (1995). It is based on parameter guesses passed in from the outer loop and choice probability predictions from the inner loop. The middle loop takes market share and churn rate predictions and finds the fixed point of the inversion equation by updating the mean flow utilities δ. The updated mean utilities are sent back to the inner loop. Therefore, convergence of the middle loop implies joint convergence of the inner loop (the individual dynamic programming problems) and the middle loop (the BLP-style inversion step). Following the literature on dynamic demand estimation I adjust the updating algorithm by a tuning parameter υ, so that:

$$f(s_t, s_{t-1}, V_t, \theta)\,[\delta_t] = \delta_t + \upsilon\,[\log(s_t) - \log(\mathscr{S}_t(s_{t-1}, \theta, \delta_t, V_t))]$$

υ is set to $1-\beta$ and dampens the adjustment of the δ-vector. The intuition for using this parameter is the following. In order to justify differences in market shares small changes in the flow utilities are sufficient because, consumers take into account not only the instantaneous payoff, but the accumulated lifetime utility of a product. After convergence the middle loop outputs values for the unobservable demand shocks $\xi(\theta)$ and the churn rate prediction errors $\zeta(\theta)$ to the outer loop.

Outer loop The outer loop takes the error terms $\xi(\theta)$ and $\zeta(\theta)$ as functions of the structural parameters and interacts them with instruments to form moment conditions.

Equilibrium multiplicity with forward-looking consumers In a model with forward-looking consumers, equilibrium multiplicity is a more problematic issue than in a myopic model unless restrictive assumptions on consumers' beliefs are imposed. Equilibrium multiplicity requires the inner loop to compute all solutions to the value function which makes it computationally much more involved. A potential solution to this problem may be to use computationally efficient homotopy methods similar to Judd, Renner, and Schmedders (2012) to find all equilibria which I leave as a topic for future research.

3.6 Results

Ex-ante it is not clear how the results of a dynamic and a myopic model would compare. For example, switching cost estimates could increase or decrease when going from a myopic to a dynamic model. This depends on a variety of factors and their interaction, among others, the joint distribution of consumer beliefs on the evolution of products' quality and firms' churn rates.

Table 3.1 and 3.2 display the results for the estimation of the dynamic model. The last column translates the point estimates into a monetary willingness-to-pay using the marginal utility of money derived from the estimated price coefficient. For the switching costs, the last column displays the monetary equivalent of a one-time utility loss from switching operators once. For the network effects, it displays the average monthly willingness to pay for an increase of an operator's market share within a consumer's reference group by 20 percentage points.

Table 3.1: Results for dynamic model (non-linear parameters)

	Point Estimates	Standard Error	P-Values	WTP in US-$
Network effect, d=1	1.5485	0.0016	0.0000	7.14
Network effect, d=2	1.7896	0.0005	0.0000	10.92
Network effect, d=3	1.1775	0.0006	0.0000	5.32
Network effect, d=4	1.2568	0.0027	0.0000	7.59
Switching cost, d=1	2.1026	0.0003	0.0000	145.45
Switching cost, d=2	5.3236	0.0010	0.0000	486.96
Switching cost, d=3	2.8735	0.0002	0.0000	194.72
Switching cost, d=4	3.7385	0.0014	0.0000	338.52

Table 3.2: Results for dynamic model (linear parameters)

	Point Estimates	Standard Error	P-Values	WTP in US-$
Local service quality, d=1	0.1000	0.0033	0.0000	6.9176
Local service quality, d=2	-0.2424	0.0039	0.0000	-22.1708
Local service quality, d=3	0.0352	0.0006	0.0000	2.3873
Local service quality, d=4	0.1202	0.0005	0.0000	10.8884
Log(subscription price), d=1	-0.0882	0.0274	0.0013	-
Log(subscription price), d=2	-0.0667	0.0208	0.0013	-
Log(subscription price), d=3	-0.0900	0.0280	0.0013	-
Log(subscription price), d=4	-0.0674	0.0210	0.0013	-

Table 3.3: Overview on consumer types and average expenditure

d	Age	Income	Monthly expenditure
1	>45	below median income	US-$ 53
2	>45	above median income	US-$ 70
3	<45	below median income	US-$ 66
4	<45	above median income	US-$ 73

3.6.1 Comparison with myopic model

Qualitatively, the results are similar to the ones obtained from the myopic model in Chapter 2. Switching costs and network effects are highly significant for all consumer types. Network effects are stronger for older and richer consumers. While older consumers with high income ($d = 2$) are willing to pay around US-$ 11 per month (15% of the average monthly wireless bill) for a 20%-point increase in an operator's market share, young and poor consumers ($d = 3$) are willing to pay only US-$ 5 (7.5% of the average monthly wireless bill) for this increase in market share. In comparison to the myopic model, network effects are on average 50% lower.

Estimates of the switching costs range from US-$ 145 (for $d = 1$, older and poor consumer) to US-$ 486 (for $d = 2$, older and rich consumers). Relatively speaking switching costs amount to roughly three to seven times the average monthly wireless expenditure. Analogously to the results for the network effect, switching cost estimates are lower than in the myopic model. For young and rich consumers ($d = 4$) switching costs decrease by 10%. For poor consumers ($d = 1$ and $d = 3$) switching costs decrease by more than 50%.

In order to compare the relative magnitude of switching costs and network effects, one can use the same thought experiment as in Chapter 2, i.e. compute the subsidy that a consumer with a time horizon of 2 years requires in order to switch from a large operator to one with identical quality and prices but 20 percentage points lower market shares. For types with high income this subsidy would have to be roughly US-$ 500 for younger consumers and US-$ 700 for older consumers. In both cases 40% of the subsidy would compensate for the foregone network effect and 60% for the incurred switching cost. For poorer consumers, the subsidy would have to be around US-$ 300 with roughly 45% of the subsidy compensating for the network effect.

Overall, the estimates from the dynamic model are slightly more plausible than the ones obtained from the myopic model. For example, in the myopic case, consumer type $d = 4$ (young and rich) had lower switching costs than young and poor consumers. In the dynamic model, this ranking changed, with richer consumers consistently having larger switching costs than poor consumers from the same age group.

3.6.2 Price elasticities

In dynamic models, there does not exist a closed-form formula for the price elasticities. Computing these requires resolving the model at different levels of prices. Tables 3.4-3.6 describe the implied price elasticities in the short-run (6 months), medium-run (2 years) and long-run (5 years). These results are based on simulating market shares for every period after an operator has permanently increased its price by 10%.

Table 3.4: Short-run price elasticities (dynamic model)

	∂s_0	∂s_1	∂s_2	∂s_3	∂s_4
∂p_1	0.4407	-1.1907	0.3115	0.4228	0.5211
∂p_2	0.4001	0.3591	-1.0096	0.3741	0.4576
∂p_3	0.4109	0.4140	0.2975	-1.5223	0.5325
∂p_4	0.2703	0.2675	0.1743	0.2719	-1.4630

Switching costs lead to relatively low own-price elasticities (around -1) in the

Table 3.5: Medium-run price elasticities (dynamic model)

	∂s_0	∂s_1	∂s_2	∂s_3	∂s_4
∂p_1	0.9684	-3.4084	1.0116	1.2671	1.2205
∂p_2	0.9573	1.2036	-3.0188	1.5029	1.3547
∂p_3	0.7236	0.8701	0.8189	-4.1900	1.0597
∂p_4	0.6134	0.6911	0.6292	0.8412	-3.7765

Table 3.6: Long-run price elasticities (dynamic model)

	∂s_0	∂s_1	∂s_2	∂s_3	∂s_4
∂p_1	1.2152	-4.6920	1.8530	1.7248	1.6065
∂p_2	1.3777	2.1051	-4.3626	2.2691	1.9675
∂p_3	0.6207	0.8479	0.9734	-5.5781	0.9327
∂p_4	0.6558	0.8578	1.0769	0.8479	-5.0709

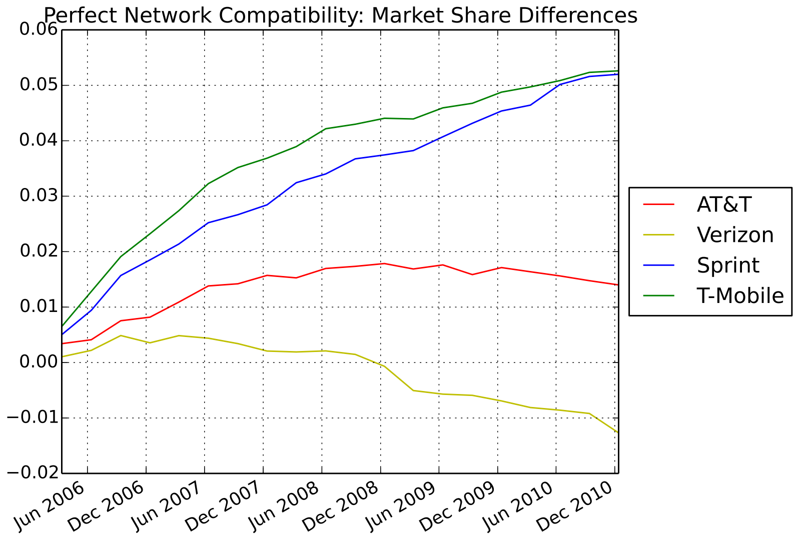
short-run with elasticities for the smaller operators being larger than for the big ones. However, short-run elasticities in the dynamic model are much larger than in the myopic model. This is very plausible given that I simulate a permanent price change. While consumers in a myopic model take into account the change only for the current period, forward-looking consumers anticipate the discounted lifetime loss of the price increase and therefore react much faster. On a two-year horizon elasticities become larger (between -3 and -4). In the long-run consumers react even more strongly to price increases with elasticities around -5.

These elasticities indicate that consumer lock-in may actually not be as strong as suggested by the large point estimates for switching costs. The long-run cross-price elasticities are generally largest for the bigger operators, i.e. no matter which carrier raises its price, consumers are much more likely to substitute to one of the two large firms. However, differences in cross-price elasticities are by far not as pronounced as in the myopic model.

3.7 Counterfactuals

In this section, I conduct a series of counterfactuals using the dynamic model to analyze how network effects and switching costs affect consumer behavior and price elasticities.

Figure 3.1: Perfect network compatibility: market share differences



Perfect network compatibility First, I simulate the following change: Carriers charge the same average subscription prices and consumer buy the same quantities as in the observed data, but the network effect works on the cumulative market share of all inside goods.

Price elasticities decrease under perfect network compatibility, but the decrease is less pronounced than in the myopic model. Especially in the long run, cross-price elasticities shift in favor of the smaller operators, in particular cross-price elasticities become largest for the smaller operators.

Large switching costs restrain consumers from adjusting immediately. Among the major four operators the effect is monotone in network size. While AT&T's market share increases by only 1 percentage point, Verizon, the biggest carrier, loses marginally until the end of the sample period. Sprint and T-Mobile gain most (about 5 percentage points in market share each); mostly on the expense of the small operators summarized in the outside good. In comparison to the myopic model, forward-looking consumers adjust more quickly to perfect network compatibility, but overall the changes in market shares are less pronounced.

As in Chapter 2, the explanatory power of the counterfactual is limited because I continue to treat the supply side and consumers' quantity choice as fixed. However, this exercise reveals that network effects continue to have a significant effect on consumer behavior when consumers' beliefs on the future industry evolution are explicitly incorporated into the model.

Table 3.7: Short-run price elasticities (dynamic model) - perfect network compatibility

	∂s_0	∂s_1	∂s_2	∂s_3	∂s_4
∂p_1	0.4403	-1.0011	0.2635	0.3764	0.4193
∂p_2	0.4339	0.2812	-0.8661	0.3472	0.3759
∂p_3	0.4447	0.3339	0.2681	-1.2109	0.4293
∂p_4	0.3606	0.2338	0.1917	0.2898	-1.3169

Table 3.8: Medium-run price elasticities (dynamic model) - perfect network compatibility

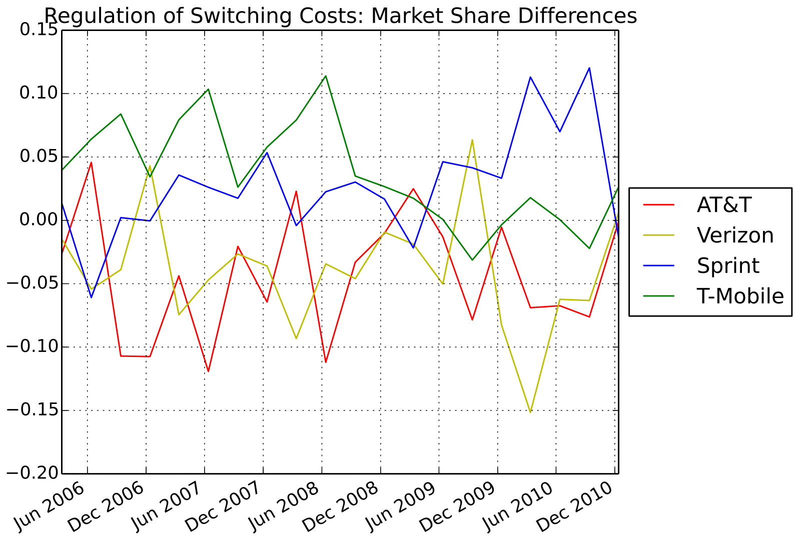
	∂s_0	∂s_1	∂s_2	∂s_3	∂s_4
∂p_1	1.3454	-2.5780	0.7690	0.9840	0.9429
∂p_2	1.3803	0.8504	-2.3924	1.0941	0.9959
∂p_3	1.2429	0.7596	0.7186	-3.1006	0.8759
∂p_4	1.2033	0.6540	0.6293	0.8189	-2.9695

Table 3.9: Long-run price elasticities (dynamic model) - perfect network compatibility

	∂s_0	∂s_1	∂s_2	∂s_3	∂s_4
∂p_1	1.6442	-3.3244	1.1476	1.3974	1.2634
∂p_2	1.6590	1.2675	-3.2497	1.5512	1.3785
∂p_3	1.2064	0.8798	0.8511	-4.0618	1.0086
∂p_4	1.3354	0.8679	0.8982	1.0739	-3.7500

Reduction of switching costs Simulating the effect of a reduction of switching costs by 50% yields mixed results. As expected, consumers react more strongly in the short-run, i.e. they react more quickly to a price increase. Moreover, the difference between medium- and long-run elasticities shrinks substantially. However,

Figure 3.2: Regulation of switching costs: market share differences



reducing switching costs seems to make demand less elastic compared to the baseline elasticities. This is counterintuitive and puzzling, but may be due to the fact that reducing switching costs results in very volatile market shares both compared to the actual market shares and compared to the counterfactual scenario with myopic consumers. The additional volatility is due to consumers having flexible beliefs on the future industry which makes the simulated price elasticities very noisy and therefore hard to interpret and compare.

In terms of market shares, the two big operators tend to lose around 5 percentage points each. The market share of the fringe remains basically unaffected. T-Mobile and Sprint would gain on average about 5 percentage points although there is no monotone trend over time. Overall, these results highlight once more the importance of switching costs for consumer behavior in the US wireless industry.

Table 3.10: Short-run price elasticities (dynamic model) - subsidized switching costs

	∂s_0	∂s_1	∂s_2	∂s_3	∂s_4
∂p_1	0.3092	-1.9614	0.4581	0.5253	0.6220
∂p_2	0.7516	0.5519	-1.7528	0.4305	0.7850
∂p_3	0.5538	0.4721	0.3334	-1.8146	0.5266
∂p_4	0.4844	0.7296	0.5107	0.4555	-2.1881

Table 3.11: Medium-run price elasticities (dynamic model) - subsidized switching costs

	∂s_0	∂s_1	∂s_2	∂s_3	∂s_4
∂p_1	0.5017	-2.1789	0.3909	0.6918	0.6688
∂p_2	0.7314	0.6624	-2.1306	0.4887	1.0947
∂p_3	0.8427	0.5801	0.4287	-2.4020	0.6481
∂p_4	0.7736	0.6230	0.5063	0.7944	-2.6036

Table 3.12: Long-run price elasticities (dynamic model) - subsidized switching costs

	∂s_0	∂s_1	∂s_2	∂s_3	∂s_4
∂p_1	0.5635	-2.1741	0.6038	0.5262	0.7725
∂p_2	0.7660	0.4815	-2.0712	0.5324	0.7726
∂p_3	0.7611	0.6851	0.2706	-2.5434	1.0899
∂p_4	0.5823	0.4043	0.5095	0.6438	-2.8126

3.8 Conclusion

In this chapter, I extended the demand model developed in Chapter 2 to a setting in which consumers are forward-looking. In high-tech consumer goods industries, it is very likely that consumers behave in a forward-looking way so that static models of consumer behavior may yield confounded results.

In a model with forward-looking consumers, the identification is more involved and relies on more restrictive assumptions than in the myopic model. For my application, I have to assume that the sequentially exogenous instruments used to identify the network effect do not enter consumers' value functions as an explicit state variable. The identification of dynamic demand models in general is still an open question and an important area for future research

The estimation results of the dynamic model indicate that both switching costs and network effects are very large and significant, but substantially lower than the estimates that come from the myopic model. Unfortunately, there is no way to rigorously test whether a dynamic or a myopic model is the right one because in my current model the discount factor is not identified. In a more extensive model, the discount factor could be identified. If one explicitly models consumers' bundle choice of a carrier and a handset, it should be possible to identify the discount factor from consumers' reaction in carrier choice to exclusive handsets that become available later in the future. A similar identification strategy is used by Lee (2013) to identify the discount factor in the video game industry.

In comparison to the myopic model, forward-looking consumers' reaction to a regulation of network effects and switching costs is smaller, but adjustment takes place much faster. This is intuitive as forward-looking consumers anticipate the future effects of contemporaneous shocks so that they should adapt immediately. The biggest caveat with the counterfactuals in both Chapter 2 and Chapter 3 is that they do not allow for any reaction on the supply side. Most importantly, I assume that carriers' pricing strategies remain unaffected in the counterfactual simulations.

In Chapter 4, I outline a model that can be used to endogenize operators' pricing strategies. In principle, this framework can be combined with both the myopic demand model in Chapter 2 as well as the dynamic model from this chapter. However, without direct information on continuation values, such as for example in Kalouptsidi (2014), estimating a full industry model with both dynamic demand and dynamic supply is likely to be computationally infeasible.

Appendix A Reformulation of the estimation in MPEC framework

The NFXP algorithm is computationally very demanding as the full model has to be solved for every guess of the parameter values. Su and Judd (2012) propose a reformulation of the estimation problem as a mathematical programming problem with equality constraints (MPEC). Conlon (2011) has applied this estimation strategy in a dynamic demand model of the LCD TV market. Instead of solving for the model equilibrium for each parameter guess, the MPEC method assures that all constraints imposed by the economic model are satisfied at the optimal solution. This estimation strategy works particularly well when the Hessian of the objective function is relatively sparse. As I estimate group-specific coefficients, this is likely to be the case in my model and I expect the MPEC form to be much more efficient than the NFXP routine. Reformulating my economic model in an MPEC context implies the following set of constraints $\forall i, j, t$:

$$Pr^i(\tilde{j}|\tilde{j}) = \frac{\exp(w^i_{\tilde{j}t})}{\exp(w^i_{\tilde{j}t}) + \exp(\Delta^i(\tilde{j}, \Omega))} \tag{3.1}$$

$$Pr^i(j|\tilde{j}) = \frac{\exp(w^i_{jt} - \psi^i)}{\exp(w^i_{jt} - \psi^i) + \exp(\Delta^i(j, \Omega))} \tag{3.2}$$

$$s^i_{jt} = \sum_{j'} P^i(j|j') s^i_{j't-1} \tag{3.3}$$

$$v^i_{\tilde{j}t} = \log[\exp(\delta^i_{\tilde{j}t}) + \beta \mathbb{E}[V^i(\delta^i_{\tilde{j}}, \Delta'^i_{\tilde{j}})|\Omega] + \exp(\Delta^i_{\tilde{j}}(\Omega))] \tag{3.4}$$

$$\Delta^i_{\tilde{j}t} = \log(\sum_{j \neq \tilde{j}} \exp(\delta^i_j - \psi^i + \beta E[V^i(j, \Omega')|\Omega])) \tag{3.5}$$

$$\mathbb{E}(\Delta^i_{jt+1}|\Delta^i_{jt}) = \hat{\gamma} \widetilde{\Delta}^i_{jt} \tag{3.6}$$

$$\mathbb{E}(\delta^i_{jt+1}|\delta^i_{jt}) = \hat{\tau} \widetilde{\delta}^i_{jt} \tag{3.7}$$

$$\hat{\gamma}^i = (\tilde{\Delta}^{i\prime} \tilde{\Delta}^i)^{-1} (\tilde{\Delta}^{i\prime} \tilde{\Delta}) \tag{3.8}$$

$$\hat{\tau}^i = (\tilde{\delta}^{i\prime} \tilde{\delta}^i)^{-1} (\tilde{\delta}^{i\prime} \tilde{\delta}) \tag{3.9}$$

Estimation adds the following constraints on observed data and model predictions :

$$s^i_{jgt} = \mathscr{S}^i_{jgt} \tag{3.10}$$

$$c^i_{jgt} = \mathscr{C}^i_{jgt} \tag{3.11}$$

Minimizing the GMM criterion function subject to these constraints yields consistent estimates of the structural parameters that are identical to ones obtained by applying a NFXP algorithm.

Appendix B Observed market shares

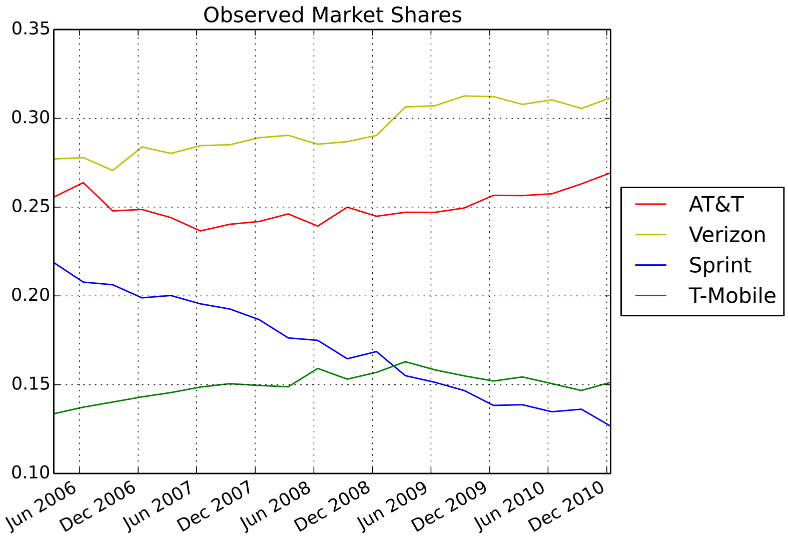
Table 3.13: Observed market shares

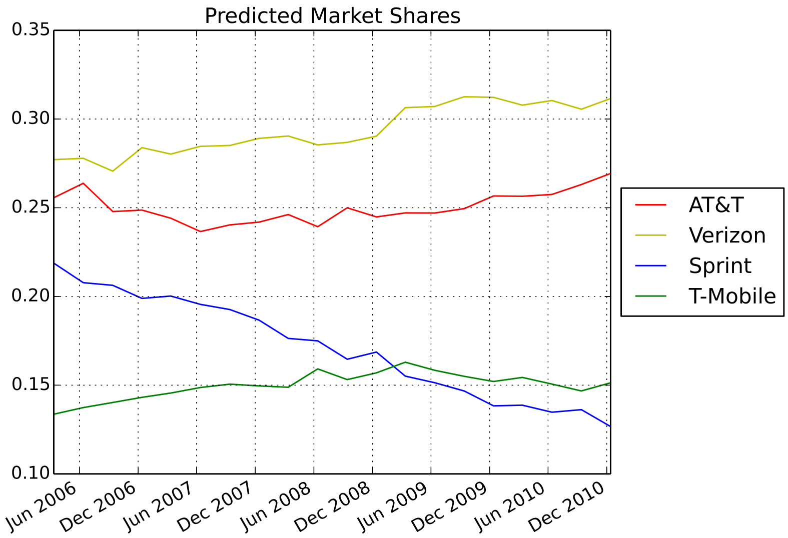
	Other	AT&T	Verizon	Sprint	T-Mobile
Q1-2006	0.1148	0.2556	0.2771	0.2188	0.1336
	0.1132	0.2638	0.2779	0.2078	0.1374
	0.1350	0.2479	0.2706	0.2063	0.1403
	0.1254	0.2487	0.2839	0.1989	0.1432
Q1-2007	0.1299	0.2441	0.2802	0.2002	0.1456
	0.1345	0.2366	0.2846	0.1956	0.1487
	0.1314	0.2403	0.2851	0.1926	0.1506
	0.1327	0.2419	0.2891	0.1867	0.1496
Q1-2008	0.1382	0.2462	0.2904	0.1764	0.1488
	0.1411	0.2393	0.2854	0.1750	0.1592
	0.1454	0.2500	0.2869	0.1646	0.1531
	0.1392	0.2448	0.2904	0.1687	0.1569
Q1-2009	0.1284	0.2471	0.3064	0.1551	0.1630
	0.1361	0.2470	0.3071	0.1514	0.1584
	0.1362	0.2495	0.3126	0.1467	0.1550
	0.1407	0.2567	0.3122	0.1384	0.1521
Q1-2010	0.1426	0.2565	0.3078	0.1387	0.1544
	0.1467	0.2575	0.3104	0.1348	0.1506
	0.1484	0.2631	0.3055	0.1362	0.1467
	0.1411	0.2693	0.3116	0.1267	0.1514

Table 3.14: Predicted market shares

	Other	AT&T	Verizon	Sprint	T-Mobile
Q1-2006	0.1151	0.2555	0.2771	0.2187	0.1337
	0.1141	0.2634	0.2777	0.2074	0.1374
	0.1336	0.2483	0.2715	0.2062	0.1404
	0.1262	0.2485	0.2836	0.1986	0.1431
Q1-2007	0.1297	0.2441	0.2806	0.1999	0.1456
	0.1329	0.2376	0.2851	0.1954	0.1490
	0.1309	0.2408	0.2853	0.1921	0.1508
	0.1323	0.2424	0.2892	0.1865	0.1496
Q1-2008	0.1377	0.2464	0.2908	0.1762	0.1488
	0.1403	0.2398	0.2858	0.1749	0.1592
	0.1461	0.2503	0.2865	0.1642	0.1529
	0.1397	0.2448	0.2902	0.1683	0.1570
Q1-2009	0.1306	0.2469	0.3051	0.1546	0.1628
	0.1384	0.2469	0.3055	0.1508	0.1584
	0.1366	0.2497	0.3122	0.1462	0.1551
	0.1404	0.2568	0.3125	0.1382	0.1522
Q1-2010	0.1432	0.2567	0.3072	0.1385	0.1544
	0.1471	0.2574	0.3101	0.1347	0.1507
	0.1501	0.2626	0.3047	0.1361	0.1466
	0.1427	0.2693	0.3104	0.1266	0.1510

Figure 3.3: Observed and predicted market shares





Appendix C Counterfactual market shares

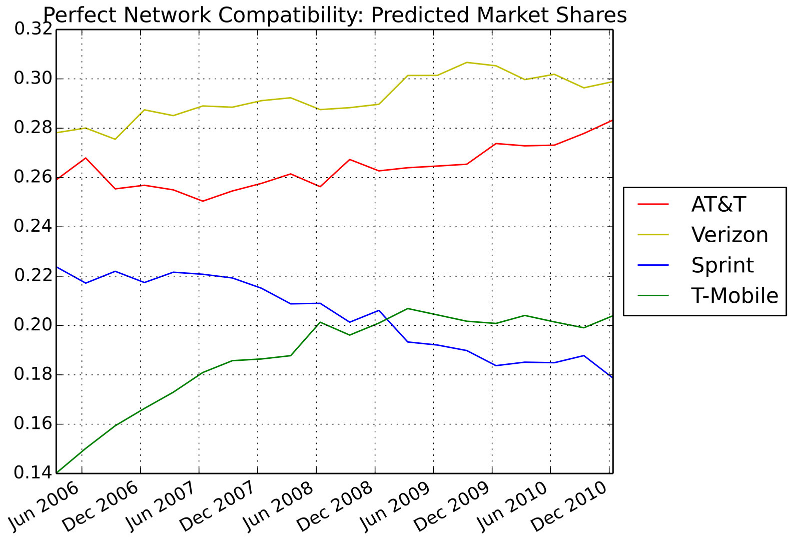
Table 3.15: Perfect network compatibility - predicted market shares

	Other	AT&T	Verizon	Sprint	T-Mobile
Q1-2006	0.0988	0.2590	0.2782	0.2238	0.1402
	0.0847	0.2679	0.2801	0.2172	0.1502
	0.0877	0.2554	0.2755	0.2220	0.1594
	0.0719	0.2569	0.2874	0.2174	0.1664
Q1-2007	0.0653	0.2550	0.2851	0.2216	0.1730
	0.0588	0.2504	0.2890	0.2208	0.1810
	0.0519	0.2545	0.2885	0.2193	0.1857
	0.0497	0.2576	0.2912	0.2151	0.1864
Q1-2008	0.0497	0.2615	0.2923	0.2088	0.1878
	0.0458	0.2563	0.2875	0.2090	0.2013
	0.0469	0.2673	0.2883	0.2014	0.1961
	0.0405	0.2627	0.2897	0.2061	0.2010
Q1-2009	0.0344	0.2640	0.3014	0.1933	0.2069
	0.0375	0.2647	0.3014	0.1921	0.2043
	0.0364	0.2654	0.3067	0.1898	0.2017
	0.0363	0.2738	0.3053	0.1837	0.2009
Q1-2010	0.0382	0.2729	0.2997	0.1851	0.2041
	0.0386	0.2731	0.3019	0.1849	0.2015
	0.0389	0.2779	0.2964	0.1878	0.1991
	0.0352	0.2833	0.2989	0.1787	0.2040

Table 3.16: Perfect network compatibility - predicted differences in market shares

	Other	AT&T	Verizon	Sprint	T-Mobile
Q1-2006	-0.0160	0.0034	0.0010	0.0050	0.0065
	-0.0285	0.0041	0.0022	0.0094	0.0128
	-0.0472	0.0075	0.0049	0.0157	0.0191
	-0.0535	0.0082	0.0036	0.0185	0.0232
Q1-2007	-0.0645	0.0109	0.0049	0.0214	0.0274
	-0.0757	0.0138	0.0044	0.0252	0.0323
	-0.0794	0.0142	0.0034	0.0267	0.0352
	-0.0831	0.0157	0.0021	0.0284	0.0369
Q1-2008	-0.0886	0.0153	0.0019	0.0324	0.0389
	-0.0953	0.0170	0.0021	0.0340	0.0422
	-0.0985	0.0173	0.0015	0.0367	0.0430
	-0.0987	0.0179	-0.0007	0.0374	0.0441
Q1-2009	-0.0940	0.0169	-0.0051	0.0382	0.0439
	-0.0986	0.0176	-0.0057	0.0407	0.0459
	-0.0999	0.0159	-0.0059	0.0432	0.0468
	-0.1043	0.0171	-0.0069	0.0454	0.0488
Q1-2010	-0.1044	0.0164	-0.0081	0.0464	0.0497
	-0.1080	0.0156	-0.0086	0.0501	0.0509
	-0.1095	0.0148	-0.0092	0.0516	0.0523
	-0.1059	0.0140	-0.0127	0.0520	0.0526

Figure 3.4: Perfect network compatibility: market shares



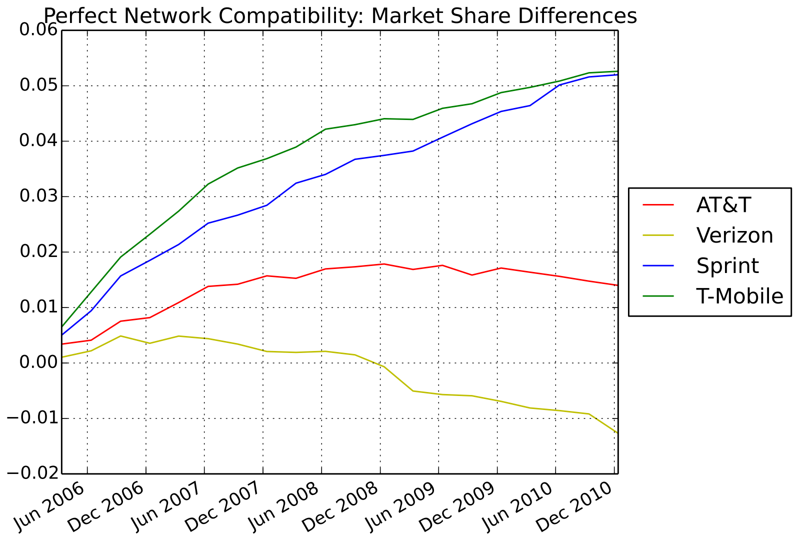


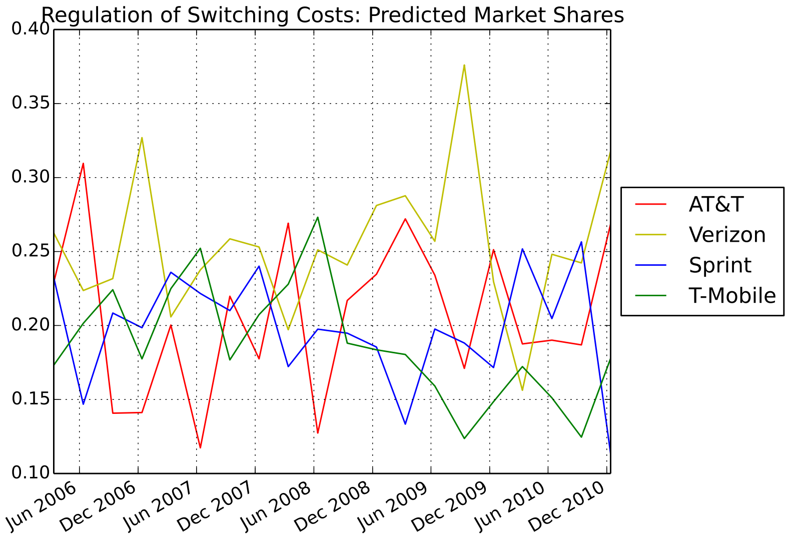
Table 3.17: Regulation of switching costs - predicted market shares

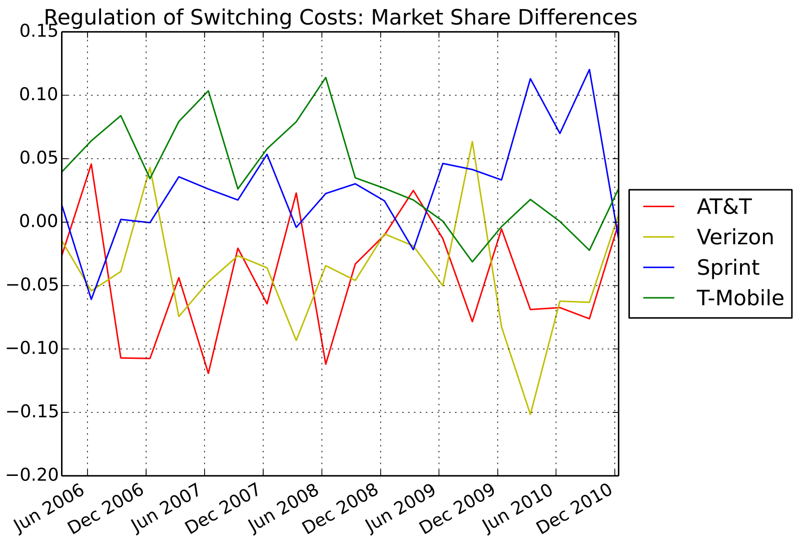
	Other	AT&T	Verizon	Sprint	T-Mobile
Q1-2006	0.1028	0.2292	0.2625	0.2323	0.1732
	0.1185	0.3096	0.2237	0.1468	0.2015
	0.1949	0.1408	0.2317	0.2084	0.2242
	0.1559	0.1412	0.3269	0.1985	0.1775
Q1-2007	0.1330	0.2003	0.2058	0.2360	0.2249
	0.1712	0.1173	0.2376	0.2217	0.2522
	0.1348	0.2198	0.2586	0.2101	0.1768
	0.1220	0.1775	0.2531	0.2401	0.2074
Q1-2008	0.1336	0.2691	0.1971	0.1722	0.2279
	0.1508	0.1273	0.2511	0.1975	0.2732
	0.1593	0.2169	0.2409	0.1948	0.1881
	0.1152	0.2346	0.2811	0.1855	0.1836
Q1-2009	0.1265	0.2721	0.2877	0.1333	0.1804
	0.1523	0.2340	0.2569	0.1976	0.1591
	0.1411	0.1711	0.3761	0.1882	0.1237
	0.1989	0.2513	0.2297	0.1716	0.1485
Q1-2010	0.2322	0.1876	0.1562	0.2518	0.1723
	0.2059	0.1901	0.2481	0.2047	0.1511
	0.1897	0.1869	0.2423	0.2565	0.1246
	0.1226	0.2685	0.3177	0.1134	0.1778

Table 3.18: Regulation of switching costs - predicted differences in market shares

	Other	AT&T	Verizon	Sprint	T-Mobile
Q1-2006	-0.0121	-0.0265	-0.0146	0.0136	0.0396
	0.0053	0.0458	-0.0542	-0.0609	0.0641
	0.0600	-0.1071	-0.0389	0.0021	0.0839
	0.0305	-0.1075	0.0431	-0.0004	0.0343
Q1-2007	0.0031	-0.0438	-0.0744	0.0358	0.0793
	0.0367	-0.1193	-0.0470	0.0261	0.1035
	0.0034	-0.0205	-0.0265	0.0174	0.0262
	-0.0108	-0.0644	-0.0360	0.0534	0.0578
Q1-2008	-0.0047	0.0229	-0.0933	-0.0041	0.0791
	0.0097	-0.1120	-0.0343	0.0226	0.1140
	0.0139	-0.0330	-0.0460	0.0302	0.0349
	-0.0240	-0.0102	-0.0093	0.0168	0.0266
Q1-2009	-0.0019	0.0250	-0.0187	-0.0218	0.0175
	0.0162	-0.0130	-0.0502	0.0462	0.0008
	0.0049	-0.0785	0.0635	0.0415	-0.0313
	0.0583	-0.0054	-0.0826	0.0332	-0.0035
Q1-2010	0.0896	-0.0689	-0.1516	0.1131	0.0179
	0.0592	-0.0674	-0.0623	0.0699	0.0005
	0.0413	-0.0762	-0.0632	0.1203	-0.0222
	-0.0185	-0.0008	0.0061	-0.0132	0.0264

Figure 3.5: Regulation of switching costs: market shares





Appendix D Differences in price elasticities

Table 3.19: Differences in short-run price elasticities - perfect network compatibility

	∂s_0	∂s_1	∂s_2	∂s_3	∂s_4
∂p_1	-0.0004	0.1897	-0.0480	-0.0464	-0.1019
∂p_2	0.0338	-0.0779	0.1434	-0.0268	-0.0816
∂p_3	0.0338	-0.0802	-0.0294	0.3114	-0.1033
∂p_4	0.0903	-0.0337	0.0174	0.0179	0.1461

Table 3.20: Differences in medium-run price elasticities - perfect network compatibility

	∂s_0	∂s_1	∂s_2	∂s_3	∂s_4
∂p_1	0.3769	0.8304	-0.2426	-0.2830	-0.2776
∂p_2	0.4230	-0.3532	0.6264	-0.4089	-0.3588
∂p_3	0.5192	-0.1106	-0.1003	1.0894	-0.1838
∂p_4	0.5899	-0.0371	0.0001	-0.0223	0.8070

Table 3.21: Differences in long-run price elasticities - perfect network compatibility

	∂s_0	∂s_1	∂s_2	∂s_3	∂s_4
∂p_1	0.4290	1.3676	-0.7054	-0.3273	-0.3431
∂p_2	0.2814	-0.8376	1.1129	-0.7178	-0.5890
∂p_3	0.5857	0.0320	-0.1222	1.5162	0.0759
∂p_4	0.6796	0.0101	-0.1787	0.2260	1.3210

Table 3.22: Differences in short-run price elasticities - subsidized switching costs

	∂s_0	∂s_1	∂s_2	∂s_3	∂s_4
∂p_1	-0.1315	-0.7707	0.1465	0.1024	0.1008
∂p_2	0.3515	0.1929	-0.7432	0.0565	0.3274
∂p_3	0.1429	0.0580	0.0359	-0.2923	-0.0059
∂p_4	0.2140	0.4622	0.3365	0.1836	-0.7252

Table 3.23: Differences in medium-run price elasticities - subsidized switching costs

	∂s_0	∂s_1	∂s_2	∂s_3	∂s_4
∂p_1	-0.4667	1.2295	-0.6207	-0.5752	-0.5517
∂p_2	-0.2259	-0.5412	0.8882	-1.0143	-0.2600
∂p_3	0.1191	-0.2900	-0.3903	1.7879	-0.4116
∂p_4	0.1602	-0.0681	-0.1228	-0.0468	1.1729

Table 3.24: Differences in long-run price elasticities - subsidized switching costs

	∂s_0	∂s_1	∂s_2	∂s_3	∂s_4
∂p_1	-0.6517	2.5179	-1.2492	-1.1985	-0.8341
∂p_2	-0.6117	-1.6236	2.2914	-1.7366	-1.1949
∂p_3	0.1404	-0.1627	-0.7027	3.0347	0.1572
∂p_4	-0.0736	-0.4535	-0.5674	-0.2041	2.2584

4 An Empirical Model of Dynamic Platform Competition in the US Wireless Industry

4.1 Introduction

This chapter complements the demand models developed in Chapter 2 and Chapter 3 with a model of the supply side. I present a model of dynamic platform competition in which firms choose prices to maximize discounted lifetime profits.

The model is similar in spirit to the theory models of Cabral (2011) and Chen (2014). In industries in which demand is driven by both switching costs and network effects, dynamically optimizing firms face a trade-off between *harvesting* and *investing*. Setting high prices will increase profits by harvesting the locked-in customers while lowering prices may be profitable because consumers are drawn to a firm's network today. Due to the presence of network effects, additional consumers are attracted to the network. This positive externality leads to a larger installed base which can be harvested in the future. As Chen (2014) has shown in numerical simulations, this trade-off crucially depends on the relative magnitude of switching costs and network effects so that different types of equilibria, for example *market tipping* or *market sharing*, may arise.

In order to keep the model tractable, I assume that each firm chooses only a single subscription price for its wireless service. Prices will be a function of the market share distribution at the beginning of the period and the (exogenously given) quality levels of all firms in the market. Even with a very restrictive state space, estimating dynamic models with strategic interaction is computationally extremely intensive. Usually, it is infeasible using methods like the nested-fixed-point algorithm because these methods require solving a complicated model for every guess of the parameter vector.

Over the last years, much more efficient two-step methods have been developed that allow to estimate dynamic games without having to explicitly compute the equilibrium. Instead, equilibrium policy functions are estimated from the data directly. Similar to Shcherbakov (2009), I propose to apply the forward-simulation method by Bajari, Benkard, and Levin (2007) to estimate carriers' marginal costs.

Combining the demand and supply side will allow for rich counterfactuals including analyzing the full industry effects of regulating switching costs or perfect network compatibility. In particular, implementing the model proposed in this chapter, would allow to investigate how firms will adjust prices in response to a regulation of switching costs or network effects and whether the market would end up in a *sharing* or *tipping* equilibrium. In addition, one may also use the model to conduct evaluations of mergers in the wireless industry.

4.2 Model

In this section, I present a dynamic model of platform competition in the US wireless industry.

4.2.1 Static model

I start by outlining a static model of Bertrand pricing competition with differentiated products. In this framework, firms' marginal costs can be easily estimated using methods as for example in Berry, Levinsohn, and Pakes (1995). It is very restrictive to assume that firms in network industries do not take into account the future. However, a static model can serve as a useful reference point. In a static model, firms will face a strong harvest motive, but they have no incentive to invest by charging a lower price today. Therefore, given fixed marginal costs, subscription prices should be unambiguously higher than in a dynamic model.

I model the supply side with 4 players: AT&T, Verizon, Sprint and T-Mobile (the four big carriers). The fringe carriers constitute the outside good whose behavior is taken as exogenously given. For simplicity, each firm offers only a single product.

Demand is modeled as in Chapter 2. Consumers subscribe to exactly one of the horizontally differentiated operators. Consumers are myopic and can switch in every period, but switching is costly. In addition to the (exogenous) technological product characteristics, consumers care about the prices charged by firms. Finally, because of the network effect, consumers derive utility from other consumers using the same carrier in this period.

In every quarter, firms maximize their per-period profit given the industry state that consists of the market share distribution at the beginning of the period and the quality characteristics of every firm. In order to simplify the notation, I assume that there is just one local market and that every consumer buys one unit of wireless service. For the estimation, one can easily incorporate multiple local markets by aggregating over all the markets and using appropriate weights. Moreover, one can allow for different consumers types buying different quantities of cellphone service.

A fundamental issue is how to define a firm's state and strategy space. Fully optimizing firms should consider the market share distribution and their quality profile on a very disaggregated level. They should base their pricing decision on the detailed demographics of their installed base and also set different prices across different market segments. In the US wireless industry, this is not observed. Carriers offer the same contracts across all local markets and to all consumer types.[1]

Therefore, I assume that firms only choose a single subscription price for a unit of phone service in a given period. In a static model one can allow firms to base pricing decisions on a very detailed and disaggregated industry state. In a dynamic model, this becomes more involved, cf. the discussion in Section 4.2.2.

The per-period profit function in period t for firm j can be written as:

$$\max_{p_j} \pi_{jt} = M_t(p_{jt} - mc_{jt})s_{jt}(p_t)$$

where p_{jt} denotes the subscription price that firm j charges, M_t is the market size and s_{jt} firm j's market share. mc denotes the marginal costs of serving an additional customer. The marginal costs are modeled as:

$$\log(mc_{jt}) = w_{jt}\gamma + \omega_{jt}$$

[1] Admittedly, there are more subtle strategies which carriers can use to price discriminate, for example by granting bonus or poaching payments. As I do not have any data on this, it is not possible to consider these subtleties in my empirical model.

where w_{jt} is a vector of observable cost shifters such as proxies for physical coverage quality or customer service. γ is a parameter vector to be estimated. ω_{jt} is a shock that is unobserved by the econometrician, but observed by firms before setting prices. As a starting point, I choose a very parsimonious specification for marginal costs with w containing only indicators for each firm, i.e. I assume that each firm has a constant marginal cost over time, but marginal costs may differ across firms. It is straightforward to let marginal costs vary with observed quality characteristics or incorporate coefficients that very over time.

The static model yields the familiar first-order conditions for every firm and every period:

$$\frac{\partial s_{jt}}{\partial p_{jt}} [p_{jt} - mc_{jt}] + s_{jt} = 0$$

$$p_{jt} = mc_{jt} - \left(\frac{\partial s_{jt}}{\partial p_{jt}}\right)^{-1} s_{jt}$$

where $\left(\frac{\partial s_{jt}}{\partial p_{jt}}\right)^{-1}$ can be computed from the underlying demand model. Substituting the expression for marginal costs, one can back out the structural cost errors ω_{jt} conditional on a guess for the cost parameters γ:

$$\omega_{jt} = \log(p_{jt} + \left(\frac{\partial s_{jt}}{\partial p_{jt}}\right)^{-1} s_{jt}) - w_{jt}\gamma$$

$$\omega_{jt} = \log(p_{jt} + \left(\frac{\partial s_{jt}}{\partial p_{jt}}\right)^{-1} s_{jt}) - \gamma_j$$

where the last line exploits the simple functional form of the marginal costs with γ_j denoting firm j's mean marginal cost.

The model predictions for ω can be interacted with instruments - in my simple case these need only be indicators for each firm - to compute a set of moments so that γ can be estimated in a GMM framework.

The static model is very easy to estimate but neglects an important aspect of the industry. In the presence of switching costs and network effects, dynamic considerations become highly important for firms, no matter whether consumers are myopic or forward-looking. In the following subsection I outline how one can incorporate this into the model.

4.2.2 Dynamic model

In a dynamic model, firms maximize discounted lifetime profits and therefore take into account the effects of their choice today on future profits. The model extension presented in this subsection is based on Shcherbakov (2009) who applies a forward-simulation approach to estimate marginal costs of cable TV firms in the US.

As in the static model, firms compete for customers in every quarter by setting subscription prices for their wireless services. In order to keep the state space tractable, I assume that firms base their pricing decisions only on their own (aggregate) market share at the beginning of the period (s_{jt-1}), the aggregate market shares of each of their competitors (s_{-jt-1}) as well as their own and competitors' quality (summarized by X_t).[2]

Admittedly, this is a restrictive assumption. It implies that firms with the same aggregate market share, but potentially different market share distributions across local markets and consumer types choose the same subscription prices. Obviously, such a strategy need not be optimal. In principle, the use of a two-step method allows to relax this assumption a bit, but not by "too much" (cf. the discussion below on estimating the equilibrium policy functions).

Assuming constant marginal costs, the per-period profit function is identical to the one from the static model:

$$\pi_{jt}(s_{jt-1}, s_{-jt-1}, p_{jt}, p_{-jt}, X_{jt}) = D_{jt}(s_{jt-1}, s_{-jt-1}, p_{jt}, p_{-jt}, X_{jt})(p_{jt} - mc_{jt})$$

with D_{jt} denoting the aggregate demand for product j. While firms choose subscription prices, quality characteristics evolve according to an exogenous $AR(1)$-process. With the simplifying assumptions on the state space, firm j's dynamic problem can

[2] The idea of using only a summary statistic of the market is similar to the concept of an *oblivious equilibrium* by Weintraub, Benkard, and Van Roy (2008).

be written as:

$$W(s_0, X_0) = \max_{p_{jt}} \mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t \pi_{jt}(p_{jt}, p_{-jt}, s_{jt-1}, s_{-jt-1}, X_{jt})\right]$$
$$s.t. \quad s_t = \mathscr{S}(s_{t-1}, p_t, X_t)$$

where s_0 denotes the market share distribution in the initial period. The expectation is taken over the evolution of the exogenous state variables $X()$ and $\mathscr{S}$ is the market share prediction coming from the demand model.

I assume that firms play a Markov Perfect Equilibrium (MPE) in subscription prices. Chen (2014) argues for a similar model that the assumptions for the proof of existence of a symmetric MPE by Doraszelski and Satterthwaite (2010) are fulfilled. A well-known problem of dynamic games is that there may be multiple equilibria. Chen (2014) deals with this problem by using an equilibrium selection rule based on the limit of a finite-horizon version of the game (Chen, Doraszelski, and Harrington Jr 2009). However, his theoretical model is much more restrictive. He allows only one customer to switch per period, whereas my demand model allows for a continuum of consumers to potentially switch every period. In that case, the problem of equilibrium multiplicity becomes much more severe. I leave the detailed discussion on this issue for future research and assume that the data used to estimate firms' cost functions come from a unique equilibrium. Under these assumptions, the dynamic problem can be written recursively with $W(s_{jt-1}, s_{-jt-1}, X_{jt})$ given by:

(4.1)
$$W(\cdot) = \max_{p_{jt}} \pi(s_{jt-1}, s_{-jt-1}, p_{jt}, p_{-jt}, X_{jt}) + \beta\mathbb{E}\left[W(s_{jt}, s_{-jt-1}, X_{jt+1} | s_{jt-1}, s_{-jt-1}, X_{jt})\right]$$

The optimal policy functions $p(s_{t-1}, X_t)$ can be obtained as the fixed point of the first order conditions (best-reply functions) of problem (4.1):

$$\frac{\partial}{\partial p_{jt}} \pi(s_{jt-1}, s_{-jt-1}, p_{jt}, p_{-jt}, X_t) + \beta\mathbb{E}\left[\frac{\partial W(s_{jt}, s_{-jt}, X_{t+1})}{\partial s_{jt}}\right] \frac{\partial s_{jt}}{\partial p_{jt}} = 0 \quad \forall j, t$$

The derivative of the per-period profit can be computed in closed-form as in the static model. The derivative of firm j's contemporaneous market share with respect to its price can be calculated as a function of consumers choice probabilities:

$$\frac{\partial s_{jt}}{\partial p_{jt}} = \sum_{k=1}^{J} s_{kt-1} \frac{\partial Pr(j|k)}{\partial p_{jt}} \tag{4.2}$$

where $Pr(j|k)$ is the conditional choice probability of choosing j after having bought product k in the previous period. If one allows for different consumer types i, one can simply compute equation (4.2) for every i. The full effect can then be computed by aggregating over all i. With α_p denoting the price coefficient in the demand function, the derivative of the choice probabilities in a logit model is given by:

$$\frac{\partial Pr(j|k)}{\partial p_{jt}} = \alpha_p \sum_{k=1}^{J} s_{kt-1} \cdot \left[Pr(j|k) - Pr^2(j|k)\right]$$

For a similar model, Shcherbakov (2009) highlights that the idea of Hansen and Singleton (1982) can be applied to form moment conditions. They exploit the fact that in a rational expectations equilibrium, firms' first-order conditions should hold in expectations at the prices observed in the data:

$$\mathbb{E}\left[h_p\right] = \mathbb{E}\left[\frac{\partial \pi}{\partial p} + \beta \frac{\partial s}{\partial p} \cdot \frac{\partial W}{\partial s}\right] = 0 \tag{4.3}$$

The most difficult challenge in this equation is to compute the derivative of the continuation values with respect to market shares. A computationally feasible approach is to combine two-step methods with forward-simulation as proposed by Bajari, Benkard, and Levin (2007) who extend the method originally proposed by Hotz and Miller (1993).

This methodology uses the observed data to estimate the equilibrium policy functions as a function of the observed state variables. Using the estimated policy functions, one can forward-simulate NS different paths of the exogenous state variables and the resulting market structure for T periods starting from any given initial state. Letting $\hat{p}()$ denote the estimates of the policy functions, the continuation values can be computed as the average over all simulated paths:

$$\hat{W}(s_{jt-1}, s_{-jt-1}, X_t) = \frac{1}{NS} \sum_{ns=1}^{NS} \sum_{t=1}^{T} \beta^t \pi(s_{jt-1}, s_{-jt-1}, X_t, \hat{p}_{jt}, \hat{p}_{-jt})$$

The derivatives of the continuation values can be calculated by finite-differences:

$$\frac{\partial \hat{W}(s_{jt}, s_{-jt}, X_{t+1})}{\partial s_{jt}} = \frac{\hat{W}(s_{jt}+\epsilon, s_{-jt}, X_{t+1}) - \hat{W}(s_{jt}-\epsilon, s_{-jt}, X_{t+1})}{2\epsilon}$$

where ϵ denotes a positive small constant.

Forward-simulation is extremely efficient, if the objective function is linear in the parameters. In this case, the simulation needs to be computed only once for every basis function. In my simple specification for marginal cost, the per-period profit can be written as a linear function of the cost parameters γ:

$$\mathbb{E}_0\left[\pi_{jt}(s_{jt-1}, s_{-jt-1}, X_t, p_{jt}, p_{-jt})\right] = \mathbb{E}\left[s_{jt} \cdot p_{jt} - s_{jt} \cdot \exp(\gamma_j)\right]$$

Therefore, it suffices to simulate two sets of basis functions:

$$\Phi_{1j}(s_{jt-1}, s_{-jt-1}, X_t, \hat{p}_{jt}, \hat{p}_{-jt}) = \frac{1}{NS}\sum_{ns=1}^{NS}\sum_{t=1}^{T}\beta^t s_{jt}\cdot \hat{p}_{jt}$$
$$\Phi_{2j}(s_{jt-1}, s_{-jt-1}, X_t, \hat{p}_{jt}, \hat{p}_{-jt}) = \frac{1}{NS}\sum_{ns=1}^{NS}\sum_{t=1}^{T}\beta^t s_{jt}$$

Consequently, the derivative can be expressed in terms of Φ:

$$\phi_{jk} = \frac{\Phi_{kj}(s_{jt-1}+\epsilon, s_{-jt-1}, X_t, \hat{p}_{jt}, \hat{p}_{-jt}) - \Phi_{kj}(s_{jt-1}-\epsilon, s_{-jt-1}, X_t, \hat{p}_{jt}, \hat{p}_{-jt})}{2\epsilon} \tag{4.4}$$

$$\rightarrow \frac{\partial \hat{W}(s_{jt-1,s_{-jt-1},X_t})}{\partial s_{jt-1}} = \phi_{j1} - \phi_{j2}\exp(\gamma_j) \tag{4.5}$$

Combining Equation 4.5 with the analytical expressions for the remaining terms in the first-order condition, one can calculate the empirical analogue of the Euler equation (4.3). Minimizing the corresponding GMM objective function will then yield consistent estimates for the marginal cost parameters γ in a dynamic model.

4.3 Estimation algorithm

The estimation algorithm consists of three steps. In the first step, equilibrium policy functions and the law of motion for the exogenous state variables are estimated from the observed data. In the second step, the set of basis functions Φ_k is computed based on the policy function estimates from the previous step and forward-simulation. In the final step, the simulated basis functions are used to construct the criterion function (the violation of the Euler equations).

Estimating policy functions and laws of motion Ideally, one would like to estimate policy functions non-parametrically. In practice, this is often tricky as the number of observations for each realization of the state space is generally too low to get reliable estimates. Therefore, I estimate the policy functions parametrically. More specifically, I assume that optimal prices are a function of the market share distribution at the beginning of the period, summary statistics of operators' quality level ($\tilde{\delta}$) and an interaction term:

$$\hat{p}_{jt} = \alpha_{0j} + \alpha_1 s_{jt-1} + \alpha_2 \tilde{\delta}_{jt} + \sum_{k \neq j} \alpha_{3k} s_{kt-1} + \sum_{k \neq j} \alpha_{4k} \tilde{\delta}_{kt} + \sum_{k} \alpha_{5k} s_{kt-1} \cdot \tilde{\delta}_{kt}$$

$\tilde{\delta}$ could be taken from the estimates of the demand model. Its law of motion is estimated assuming a stable $AR(1)$-process:

$$\tilde{\delta}_{djmt} = \eta_{0j} + \eta_{1j} \tilde{\delta}_{djmt-1} + \epsilon_{djmt}$$

In this specification, I allow the quality level to evolve differently across different segments of the market. The value of the aggregate state variables can be calculated by aggregating using the observed weights w_{dm} of different market segments.

Forward simulation step Afterwards, one can simulate forward to compute the continuation values at every value of the state variables after having discretized the state space appropriately. In order to compute the continuation values, I need to generate NS different paths of the industry over T time periods. Using the simulated series of quality characteristics, the estimated policy functions for subscription prices from the first step and the parameters from the demand model, one can simulate the industry structure for T periods and compute the discounted sum of profits. T is chosen big enough so that the discounted per-period profit $\beta^T \pi_t$ becomes very small and does not affect the continuation value anymore.

Afterwards, one can compute $\hat{W}(s_{jt-1}, s_{-jt-1}, X_t)$ and $\frac{\partial \hat{W}(s_{jt}, s_{-jt}, X_t+1)}{\partial s_{jt}}$ as the average over all simulated paths. As the profit functions can be written as a linear function of the marginal cost parameters, if suffices to run the simulation only once and use the same basis functions for all guesses of the parameter vector.

Data requirements The supply side model can be estimated using the same data that was used to estimate demand. It does not require any additional data.

4.4 Outlook and conclusion

In this chapter, I sketched an empirical model of dynamic platform competition in the wireless industry. When demand is characterized by both switching costs and network effects, firms face a non-trivial trade-off between harvesting their locked-in consumers by setting high subscription prices and investing in its customer base by charging low prices.

This trade-off has important implications for the industry dynamics. Therefore, static models are inappropriate to analyze firm behavior. Nevertheless, a static model can serve as a useful starting point. For example, marginal cost estimates from such a model should be lower than the ones obtained from a dynamic one. As the static first-order conditions ignore firms' investment incentives, they will prescribe a higher markup than the dynamic optimality conditions. In order to justify the same observed prices, a dynamic model should result in higher marginal cost estimates.

The estimation of a dynamic model is computationally very involved. The combination of two-step methods to estimate equilibrium policy functions and forward-simulation techniques to compute continuation values makes the estimation of firms' marginal costs in a dynamic framework feasible. In network industries, equilibrium multiplicity remains a severe problem, however. A detailed discussion of this issue goes beyond the scope of this thesis and is a highly interesting area for future research.

Combining the supply side framework of this chapter with the demand model from Chapter 2, allows for a broad range of highly interesting counterfactuals. In particular, one can analyze how firms react to the regulation of important industry characteristics such as switching costs and network effects. In addition, it allows to evaluate the potential effects of mergers in network industries which is a heavily debated topic in countries all over the world.

There are several directions in which one can extend the model of this chapter. Regarding the wireless industry, there are two issues that are not very much explored by academic research but that industry experts are concerned about: endogenous switching costs and endogenous quality levels. For simplicity, the model of this chapter takes both as exogenously given. In reality, carriers can basically choose the level of switching costs and their product quality. Extending models of the wireless industry in these directions is a very promising area for future research.

In conclusion, this chapter is a first but important step to empirically analyze firms' dynamic pricing strategies in network industries. Given the growing importance of these markets, they are an excellent field for future theoretical and empirical research.

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