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Network Effects and Switching Costs in the US Wireless Industry

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Network Effects and Switching Costs in the US Wireless Industry

Disentangling sources of consumer inertia

Stefan Weiergräber*

November 17, 2014

Abstract

I develop an empirical framework to disentangle different sources of consumer inertia in the US wireless industry. The use of a detailed data set 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. Being able to separate switching costs and network effects is important as both can lead to inefficient consumer inertia, but depending on its sources policy implications may be very different. Estimates of switching costs range from US-$ 316 to US-$ 630. The willingness to pay for a 20%-point increase in an operator's market share is on average US-$ 22 per month. My counterfactuals 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.

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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 the paper, 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 what 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 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 separately for 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, e.g. by Kim and Kwon (2003) and Kim et al. (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 et al. (1995) complemented with dynamic panel techniques and elements from the dynamic demand literature. For example, Shcherbakov (2013) and Nosal (2012) 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 3 presents the economic model. Section 4 describe the data used for the estimation. Section 5 develops the identification arguments and outlines the estimation strategy. Estimation results and counterfactual experiments are presented in Sections 6 and 7. Section 8 concludes.

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

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

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, e.g. 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, e.g. 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 plus some included number of *anytime minutes* that can be used to make calls at any time to any network (e.g. 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 to continuously to slightly above 50% at the end of my sample period (December 2010). After the end of my sample period, 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

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

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, e.g. 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).

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.

[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.

Consumers have heterogeneous preferences as a function of their individual demographic characteristics d. This results in a discrete number of consumer types which may e.g. 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, e.g. 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 $s^{r_d}_j$, the market share of operator j in the reference group of consumer d. If affects a consumers 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 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.

[4]Similar ideas underlie Hoernig et al. (2014), Birke and Swann (2006) and Maicas et al. (2009).

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]

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, e.g. 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

[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.

mean flow utilities δ and the switching cost parameters ψ:

$$Pr^i(\text{not switch}) = Pr^i(j|j) = \frac{\exp(\delta^i_{jt})}{\exp(\delta^i_{jt}) + \sum_{l\neq j}\exp(\delta^i_{lt} - \psi^i)}$$

$$Pr^i(\text{switch from } k \text{ to } j) = Pr^i(j|k) = \frac{\exp(\delta^i_{jt} - \psi^i)}{\exp(\delta^i_{kt}) + \sum_{l\neq k}\exp(\delta^i_{lt} - \psi^i)}$$

Consequently, market share predictions can be solved for recursively:

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

These market share and (analogously churn rate) predictions can be taken to the data to form moment conditions.

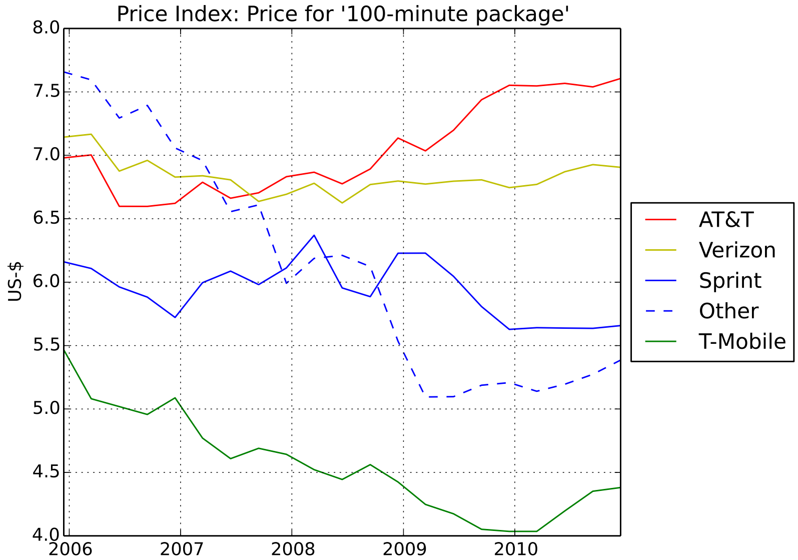
4. Data

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. Most importantly, I use these data to construct average price indices for each operator and quarter from usage and revenue data. In addition, I consider information on the cost side, e.g. 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 each quarter. The survey is stratified in order to allow for a representative

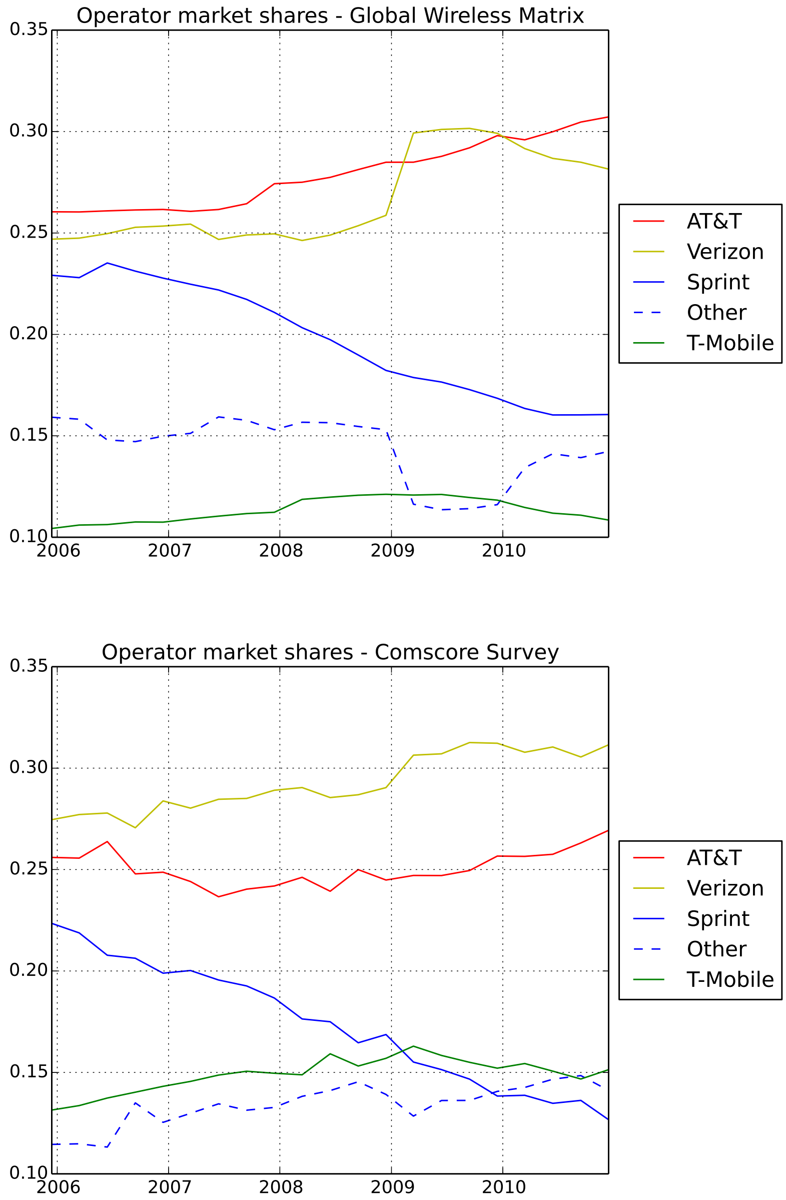
Figure 1: Constructed price index



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 cellphone bill. Unfortunately, the data do not contain detailed information on the specific pricing structure of each contract. Previous papers on the cellphone 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, e.g. 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 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

Figure 2: Comparison of market shares: survey sample vs. GWM



structures, an average price index may actually be what consumers take into account. 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 et al. (2011) by modeling usage quantity as the outcome of a static optimization problem over quantity.

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 a 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 1. The first two columns display consumers' age (in years) and yearly household income (in US-$ 1000) 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 cellphone operator within a month.

Table 1: Descriptive Statistics: Consumer type characteristics

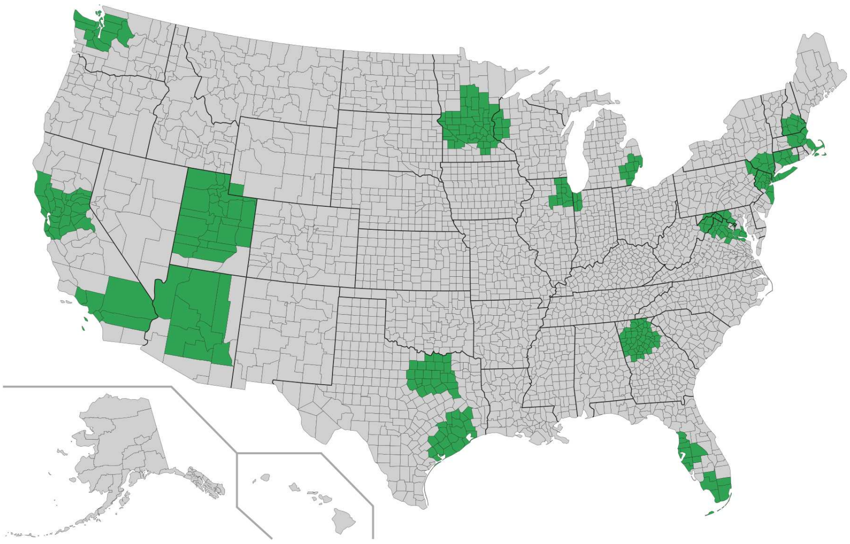
ctype	Statistic	Age	Income	Expenditure	MoU100	Switch
>45 years-poor	Mean	56.24	29.33	53.08	8.70	0.03
>45 years-poor	SD	13.45	11.73	32.71	5.63	0.16
>45 years-rich	Mean	53.41	87.89	69.75	11.02	0.02
>45 years-rich	SD	12.34	21.59	32.49	5.41	0.13
<45 years-poor	Mean	24.00	27.50	66.32	11.13	0.05
<45 years-poor	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 et al. (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 17 in the Appendix.

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) and the biggest local markets (see Table 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, e.g. 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, e.g. 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 3.

Figure 3: Overview of local markets used in the estimation



5. Identification and Estimation

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 et al. (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 5.1. *Conditional on a consumer type d, consumers have homogeneous preferences. Preferences are constant across time or local markets (or both).*

Assumption 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 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:

$$\delta^d_{jmt} = X^d_{jmt}\beta^d + \gamma^d p^d_{jt} + \alpha^d s^{r_d}_{jmt} + \xi^d_{jmt} \tag{1}$$

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. Very similarly to 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 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 1 and network effects could not be identified.

My key assumption for identifying a localized network effect is Assumption 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_{mt}^{-d} shifts the mean utility for type d in period t directly, $s_{mt-1}^{r_d}$ is excluded from the utility of type d in period t. Lagged market shares of type d affect s_{mt}^{d} and δ_{mt}^{d} 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_{mt-1}^{-d}, will affect s_{mt}^{d} 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 $s_{mt}^{r_d}$ as long as there is some sort of state-dependence in consumer choices. Lagged market shares of types $-d$ would be uncorrelated with ξ_{mt}^{d} 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 types 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, e.g. 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 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 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 mitigate this problem, note that any unobserved quality attribute, call it υ^d_{jmt}, will enter into the structural demand error $\tilde{\xi}$.

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

[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.

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, e.g. 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]

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

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:

$$f(s_t, s_{t-1}, \theta)[\delta_t] = \delta_t + \log(s_t) - \log(\mathscr{S}_t(s_{t-1}, \theta, \delta_t)) \tag{2}$$

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 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. 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

[8] In robustness checks, I searched for fixed points of equation 2 starting from several different starting values and always converged to the same solution.

prediction error ζ, i.e. the difference between predicted and observed churn rates:

$$c^d_{jmt} - \mathscr{C}^d_{jmt}(\delta_t, \psi) = \zeta^d_{jmt} \tag{3}$$

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:

$$\rightarrow \xi^d_{jmt} = \delta^d_{jmt} - X^d_{jmt}\beta^d - \gamma^d p^d_{jmt} - \alpha^d s^{r_d}_{jmt} \tag{4}$$

$$\rightarrow \nu^d_{jmt} = \xi^d_{jmt} - \iota\xi^d_{jmt-1} \tag{5}$$

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 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

[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 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. As instrument I use short-run variable cost per subscriber. 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. A consumer's reference 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

Table 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

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, e.g. 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 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 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

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

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 comes 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.

6. Results

Tables 3 and 4 display the results for the model specified in the previous section. 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%-points. Almost all coefficients have the expected sign 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 increase in an operator's local market share by 20%-points, which is the typical difference in market shares between one of the two big operators and the

Table 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 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

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 cellphone plans in the US (cf. Table 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

Table 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

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 providers compares her current operator with another operator with the same quality but 20 %-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.

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 re-solving the model at different levels of prices. Tables 6-8 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 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 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 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.

6.2. Comparison with restricted models

Table 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 10: Comparison with restricted models - WTP

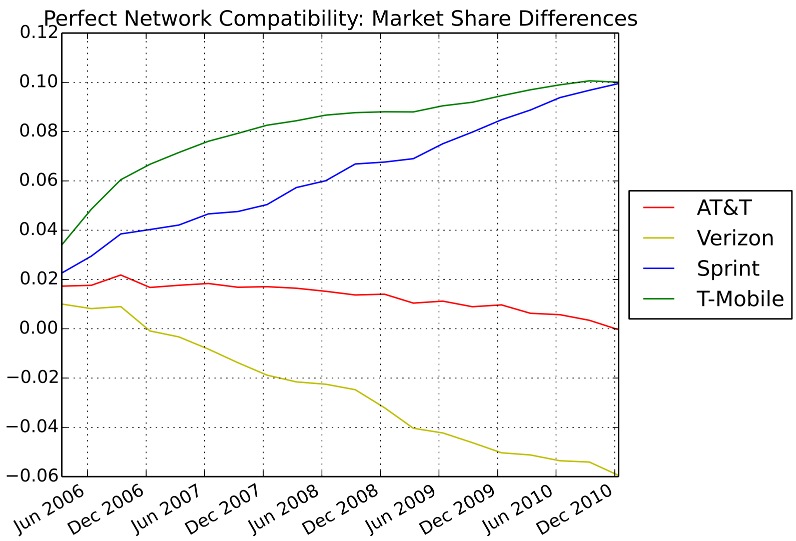
	Full Model	No network effects	No switching costs
Network effect, d=1	18.8711	-	-9.6357
Network effect, d=2	24.0523	-	-31.7323
Network effect, d=3	17.9812	-	-12.8395
Network effect, d=4	25.8078	-	-19.7294
Switching cost, d=1	316.7690	714.1376	-
Switching cost, d=2	626.2952	941.6527	-
Switching cost, d=3	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 9 and 10 display a comparison between the unrestricted model and the two restricted ones. Indeed, 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.

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 4: Perfect network compatibility: market shares



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, e.g. due to a price increase. Own-price elasticities become only slightly more homogeneous across operators. More interestingly, cross-price elasticities become significantly 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 my 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. Endogenizing consumers' quantity choice and the supply side goes beyond the scope of this paper, but is an important topic that I plan to pursue in future research. Nevertheless, this exercise reveals that network effects have a significant effect on consumer behavior in the wireless industry.

Table 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

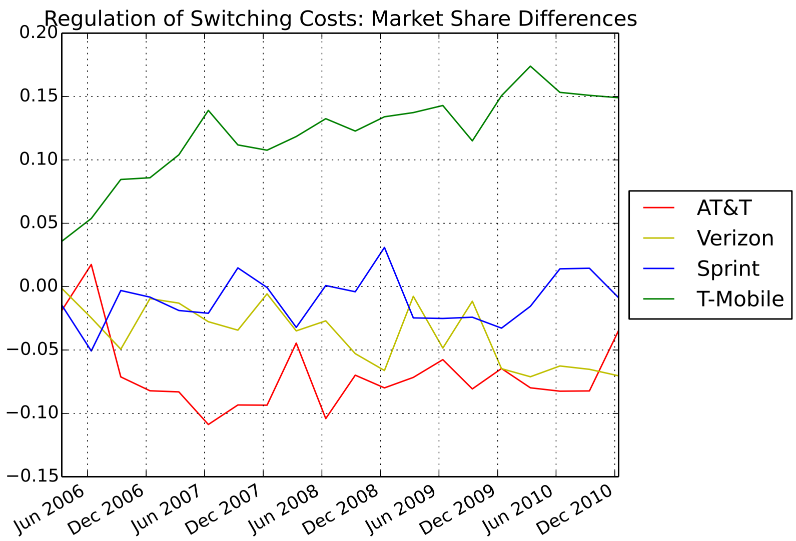
Table 12: Medium-run price elasticities - perfect network compatibility

	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 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

Figure 5: Regulation of switching costs



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. From an operator's point of view, consumer switching costs could be overcome by subsidizing switching, e.g. 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 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 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 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.

8. Conclusion

In this paper, 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 et al. (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 a companion paper (work in progress) I show how the framework can be generalized to a model in which consumers are forward-looking and have dynamic beliefs about the future industry evolution as in Gowrisankaran and Rysman (2012). 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 et al. (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). I plan to investigate the empirics of dynamic platform competition in future research. 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 more than 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 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.

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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:

$$\delta^d_{jmt} = (X^d_{jmt}\beta^d + \gamma^d p^{\text{on}}_{jt} + \tilde{\alpha}^d s^{r_d}_{jmt} + \xi^d_{jmt})q^d_{jmt} + \gamma^d(p^{\text{off}}_{jt} - p^{\text{on}}_{jt})q^{d,\text{off}}_{jmt} \tag{6}$$

$$\frac{\delta^d_{jmt}}{q^d_{jmt}} = (X^d_{jmt}\beta^d + \gamma^d p^{\text{on}}_{jt} + \tilde{\alpha}^d s^{r_d}_{jmt} + \xi^d_{jmt}) + \gamma^d(p^{\text{off}}_{jt} - p^{\text{on}}_{jt})(1 - f(s^{r_d}_{jmt})) \tag{7}$$

$$\tilde{\delta}^d_{jmt} = X^d_{jmt}\beta^d + \gamma^d p^{\text{off}}_{jt} + \tilde{\alpha}^d s^{r_d}_{jmt} - \gamma^d((p^{\text{off}}_{jt} - p^{\text{on}}_{jt}))f(s^{r_d}_{jt}) + \xi^d_{jmt} \tag{8}$$

$f(s^{r_d}_{jt}) = \frac{q^{d,\text{off}}_{jmt}}{q^d_{jmt}}$ 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 8 simplifies to:

$$\tilde{\delta}^d_{jmt} = X^d_{jmt}\beta^d + \gamma^d p^{\text{off}}_{jt} + \underbrace{(\tilde{\alpha}^d - \gamma^d(p^{\text{off}}_{jt} - p^{\text{on}}_{jt}))}_{\alpha^d} s^{r_d}_{jmt} + \xi^d_{jmt} \tag{9}$$

Equation 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 8 to the data instead of the equation used in my estimation.

B. Additional tables

B.1. Descriptive statistics

Table 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 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

B.2. Differences in price elasticities

Table 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 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 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 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 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

C. Market share graphs and tables

Table 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

D. Empirical evidence on contract structure and calling patterns

Figure 9 and 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

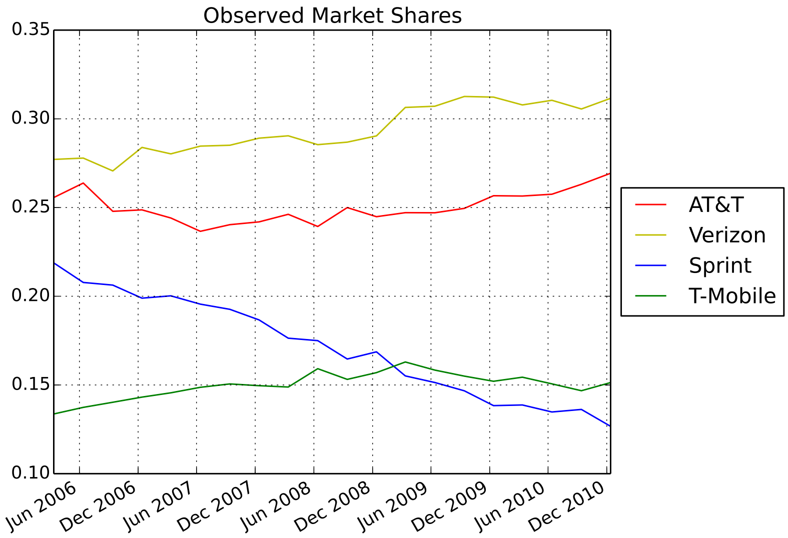
Table 25: Observed market shares

	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 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 6: Observed and predicted market shares



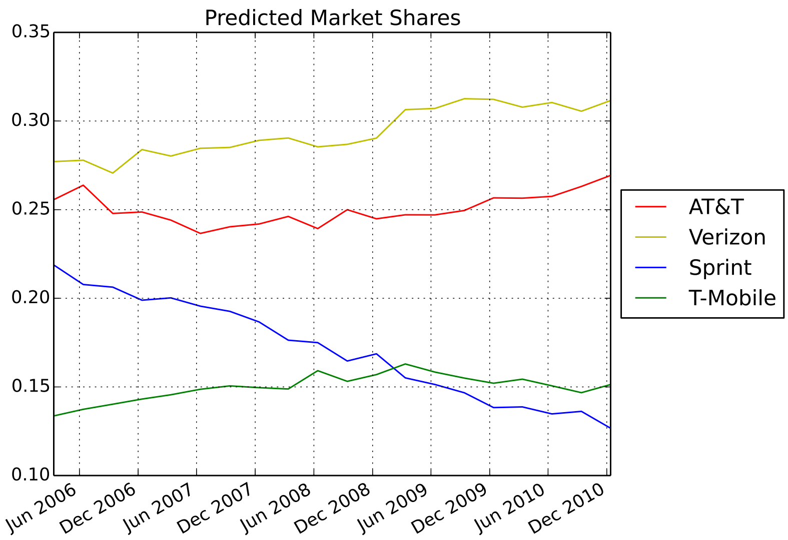


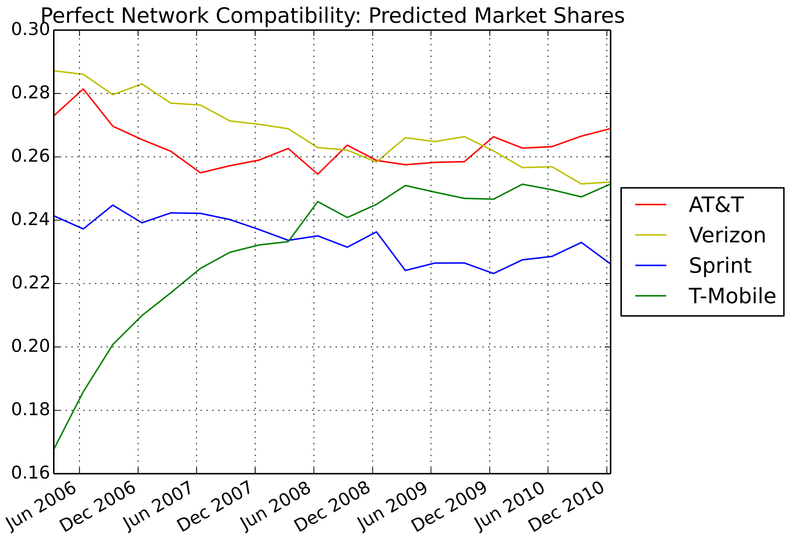
Table 27: Perfect network compatibility - predicted market shares

	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 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 7: Perfect network compatibility: market shares



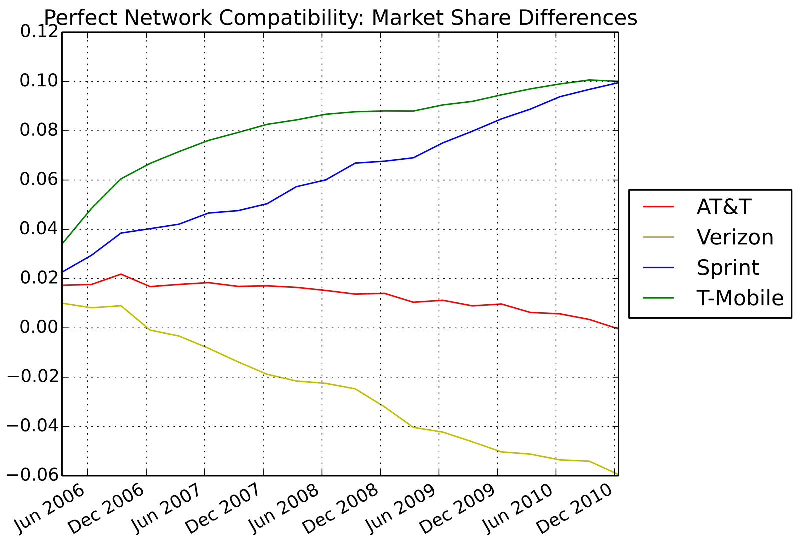


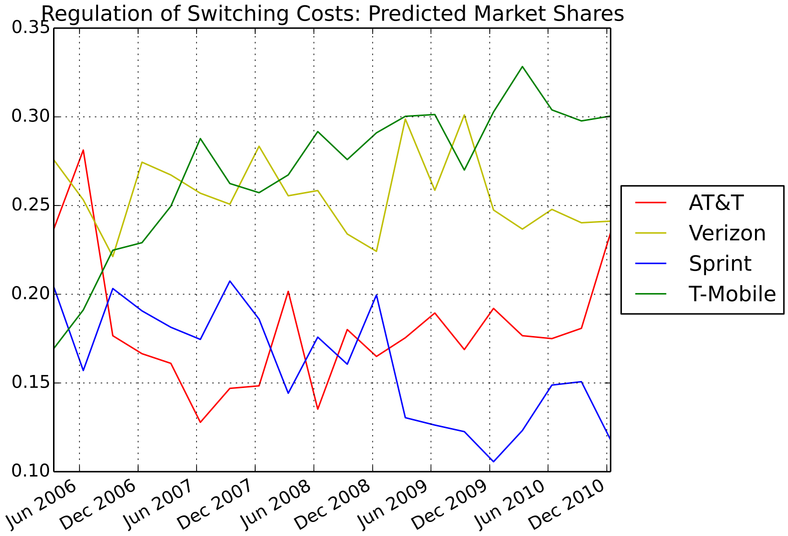
Table 29: Regulation of switching costs - predicted market shares

	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 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 8: Regulation of switching costs: market shares



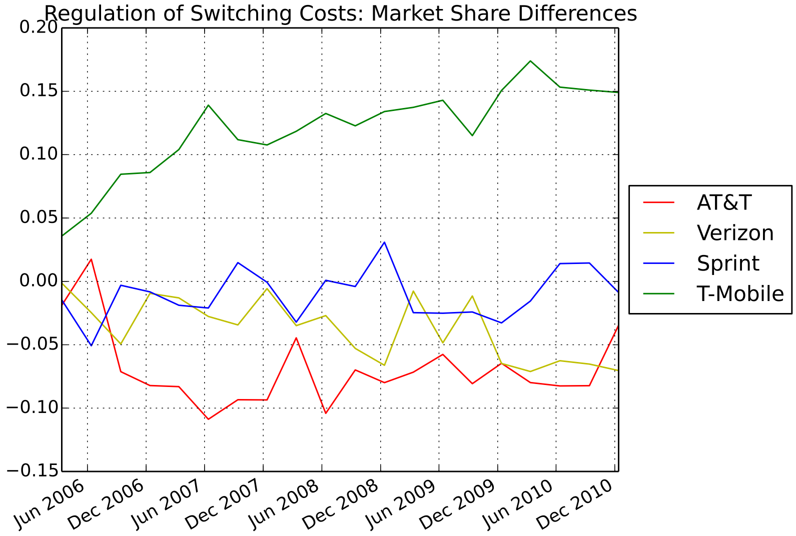
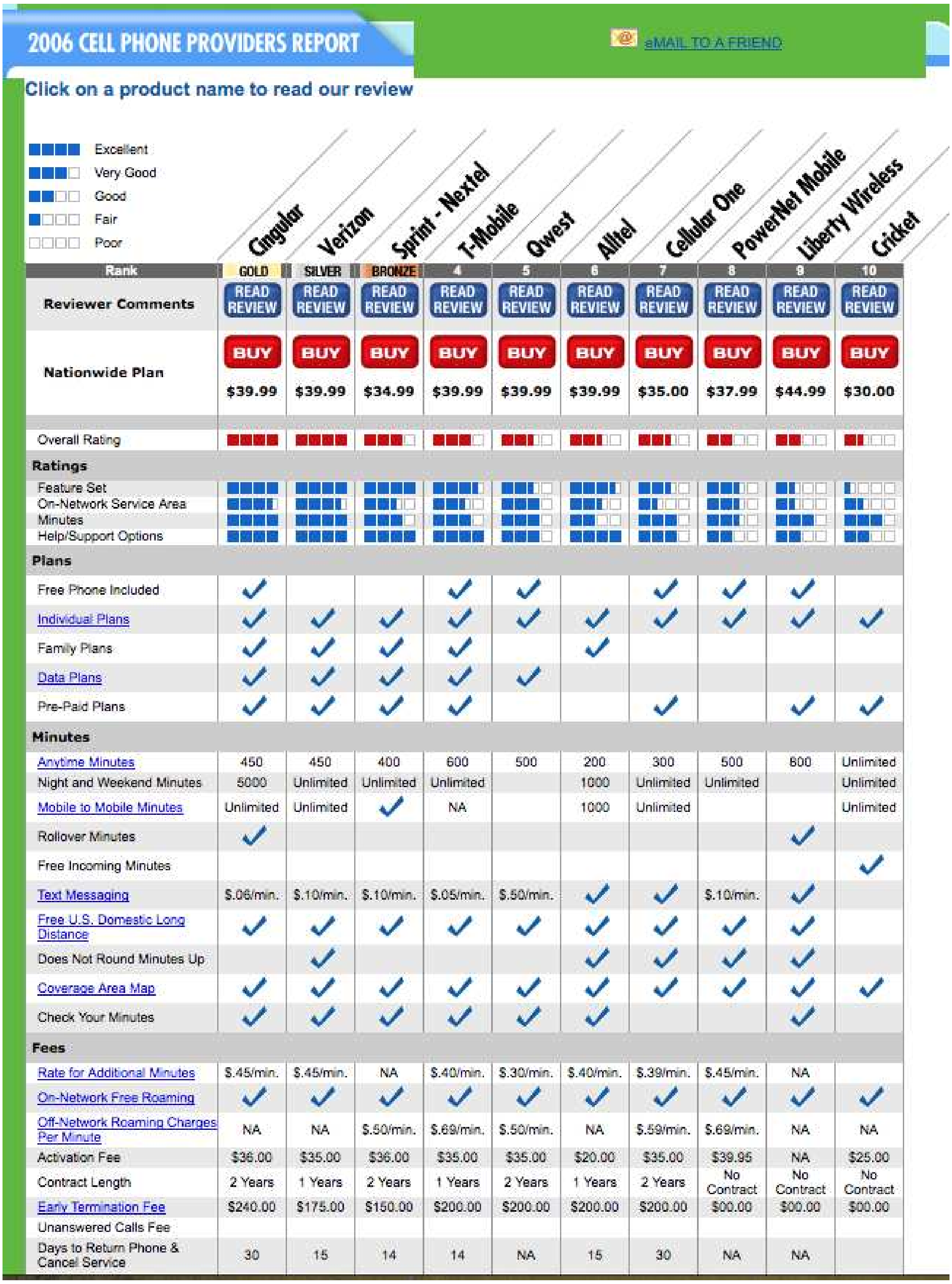


Figure 9: Information on wireless contracts from 2006



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 10: Information on wireless contracts from 2008

2008 CELL PHONE PROVIDERS REPORT

eMAIL TO A FRIEND

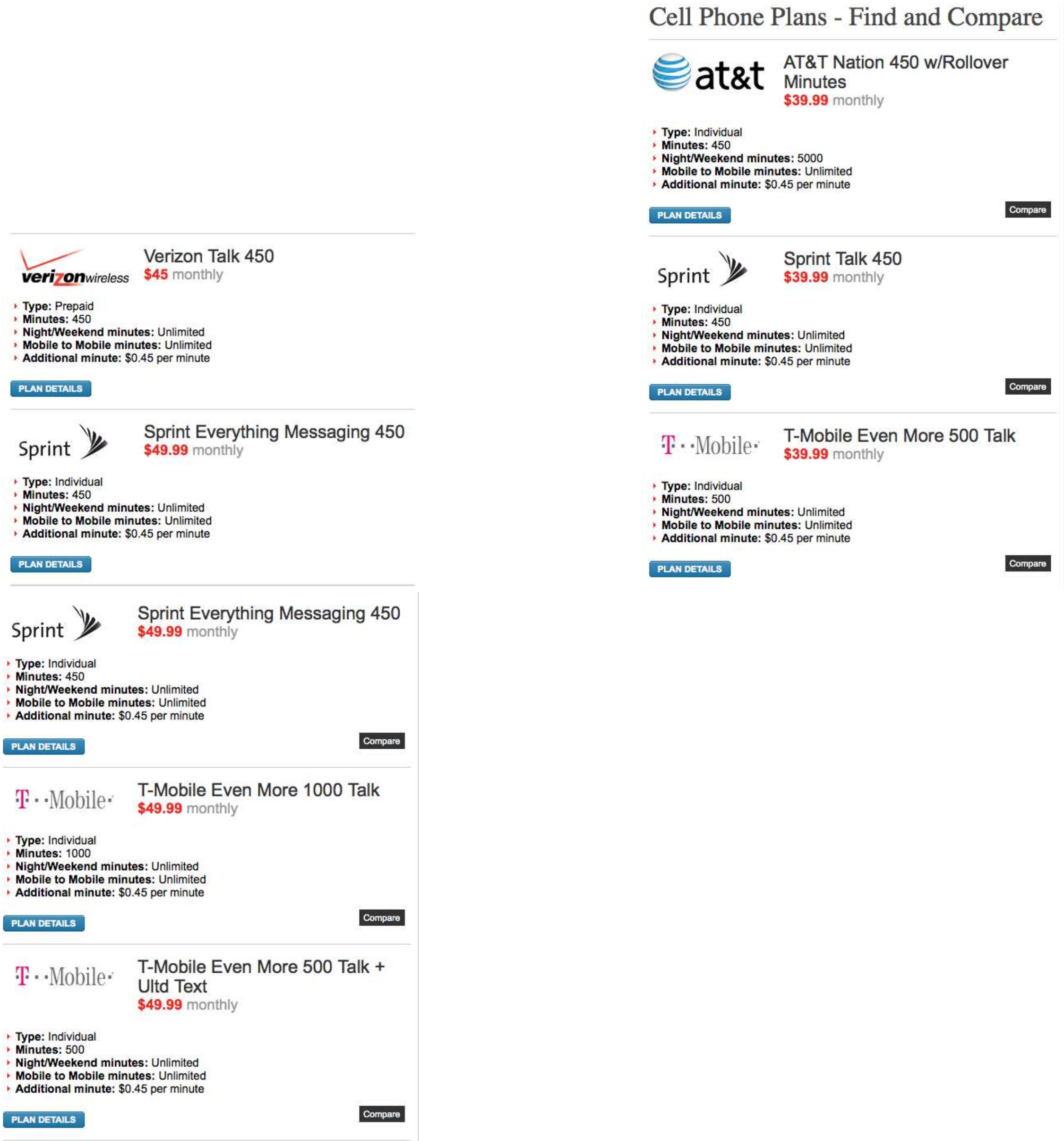
Click on a service to read our review

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										

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

Figure 11: Information on wireless contracts from 2011



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