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JEL Classification: D12, L11, L13, L40, L96

Keywords: Switching Costs, perfect foresight, structural estimation, dynamics

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The Welfare Effects of Early Termination Fees in the US Wireless Industry*

Joseph Cullen† Nicolas Schutz‡ Oleksandr Shcherbakov§

November 25, 2020

Abstract

We develop and estimate a dynamic structural model of the US wireless industry. The demand model features two sources of dynamics: First, consumers that switch contracts must pay early termination fees to their current wireless service provider; second, handsets are durable. Consumers and wireless carriers are forward-looking and, in contrast to previous work, have perfect foresight over the evolution of the industry. Carriers compete using open-loop strategies. Counterfactual simulations reveal that the elimination of early termination fees, despite raising equilibrium prices, unambiguously benefits consumers. Firms may benefit as well provided the cost of processing early termination fees is high enough.

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1 Introduction

Acquiring and retaining customers is a central objective for firms. One strategy a firm may employ to protect its customer base is to create exit barriers for existing consumers. This can be done by introducing strategic incompatibilities, creating artificial network effects, or

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explicitly writing contracts embodying switching costs. Klemperer (1995) argues that such switching costs may result in substantial welfare losses, and suggests that regulators work to reduce them. However, more recent theoretical and empirical work (e.g., Dube, Hitsch, and Rossi, 2009) emphasizes that consumers may benefit from the presence of switching costs, as firms may compete more aggressively to acquire or poach them.

Switching costs are embodied in most wireless service contracts through early termination fees (ETFs), which penalize consumers for leaving their wireless provider before the end of their multi-year contract. Wireless connectivity has become increasingly important. In 2014, revenues in the mobile telephony market exceeded 200 billion dollars per year representing 355 million unique subscribers (CTIA, 2015), and more than 45 percent of US households relied on a wireless phone as their only phone line (Blumberg and Luke, 2015). It is also increasingly common for wireless service to be an individual's primary connection to the internet (Pew Research Center, 2015). Concerns about the competitiveness of the market are thus paramount. In 2011, a major merger between the second and fourth largest carriers was blocked by the US Department of Justice due to its potential anti-competitive effects. However, as consumer advocates pointed out, having many firms in the market may not make much of a difference if the cost of switching providers curtails competition between carriers.

Wireless providers argue that ETFs are necessary due to phone subsidies: Signing a long-term contract allows the consumer to buy a handset at a subsidized price. Firms argue that they only use ETFs to prevent consumers from buying a phone at a subsidized rate and then immediately canceling their contract, leaving the firm with no opportunity to recoup its subsidy through monthly service fees. Yet, the structure of ETFs suggest that firms also use them strategically. Since each month the firm recovers a part of the cost of subsidizing the handset, the early termination fee decreases over time. However, in practice ETFs decrease slowly and remain substantial even in the final month of the contract.[1]

It is safe to say that ETFs are widely unpopular with consumers. As such, they have come under scrutiny by federal regulators and legislators, and have been the subject of high-profile, class-action lawsuits[2]. However, it is not clear that consumers are worse off with ETFs as firms are likely to set different prices depending on whether ETFs are used. For similar reasons, it is not clear that producers benefit from ETFs. This may seem counterintuitive: Since firms are *choosing* to have ETFs, should we not expect them to be better off with ETFs? This might not be the case if, e.g., there are multiple equilibria.

As a first step to study these and related questions, we develop a stylized theoretical model where firms endogenously choose whether to have ETFs and then compete in per-period

[1]Recent theoretical work has shown how an incumbent can profitably use ETFs to deter entry (Bedre-Defolie and Biglaiser, 2017). By contrast, we take the set of firms as given and focus on the effects of ETFs on pricing incentives and market performance.

[2]https://docs.fcc.gov/public/attachments/FCC-16-54A1.pdf

prices. We find that in equilibrium either all firms will have ETFs or none of the firms will have them; moreover, the ETF and no-ETF equilibria coexist for plausible parameter values, so that firms face a coordination problem. This stylized model delivers important insights. First, competition in service fees is *more intense* when ETFs are used. The intuition is that consumers perceive products as being less differentiated when ETFs are imposed: Although a consumer knows her current match values for the various alternatives when making her purchase decision, those values may change in the subsequent periods during which she will be locked in. Second, consumers may or may not be worse off in the ETF equilibrium, depending on whether the benefits they derive from lower prices are offset by their inability to switch to better alternatives when their match values change. Third, the use of ETFs is an equilibrium phenomenon and there is no reason to expect it to be a dominant strategy for firms. In particular, firms may be worse off in the ETF equilibrium due to the lower prices that arise.

Against this theoretical background, we empirically investigate the effects of ETFs on competition and welfare. Using a detailed consumer survey from 2005 to 2012, we estimate a dynamic demand model with forward-looking consumers. The data contain individual-level information on purchase decisions, consumer demographics, and handset characteristics. Individual-level data allow us to accommodate some consumer heterogeneity by allowing parameters to vary flexibly across demographic groups. The demand model is a literal application of the Berry, Levinsohn, and Pakes (1995) (BLP) model to a dynamic setting: Just like BLP assumes that consumers have perfect information about product characteristics in a static setting, our model assumes that consumers know the characteristics of all the products in the market both now and in the future. This perfect-foresight approach differs from prior work in the dynamic demand literature, as discussed in detail below.

Our structural model accounts for two important sources of dynamics: handset durability and switching costs (ETFs).[3] Importantly, we do not estimate the "hassle" costs associated with switching providers, but instead focus on the explicit contractual switching costs by including data on actual ETFs in the model. Because there is no extra hassle cost to estimate, identification in our model is more transparent. Focusing only on ETFs can be viewed as estimating a lower bound on switching costs. It is worth noting that prior work that does estimate total consumer switching costs in the industry finds estimates that are very close to the average ETF in service contracts (see Cullen and Shcherbakov, 2010).

The final step of the paper is to simulate counterfactual scenarios to investigate whether firms or consumers would be better off without ETFs. The results are particularly interesting since the industry recently transitioned to a business model without ETFs. We provide a set of counterfactual simulations within both partial and full equilibrium analysis.

[3]Another source of dynamics that is accounted for is that monthly service fees are fixed in long-term contracts, so that, for a given product, the current service fee may depend on the period of purchase.

Our partial equilibrium analysis suggests that the elimination of ETFs would increase consumer welfare by 76 percent if handset prices and service fees remained unchanged. This is only a partial equilibrium result since carriers would undoubtedly adjust those prices. In particular, without ETFs firms may stop subsidizing handsets. However, even if consumers face the full, unsubsidized handset prices, the increase in consumer surplus is still estimated to be at 48 percent when monthly service fees remain unchanged. Moreover, to offset this increase in surplus, service fees would have to increase by at least 32 percent. The question is thus whether the elimination of ETFs would trigger significant increases in service fees.

To simulate a full-equilibrium scenario where service fees endogenously adjust, we specify a supply-side model. For the sake of computational feasibility, we assume that each service provider uses an open-loop strategy (see, e.g., Chapter 4 in Fudenberg and Tirole, 1991), thus choosing once and for all the prices of all of its products in all time periods to maximize the present discounted value of its profits.[4] The marginal costs of providing each product are recovered in a way similar to Berry, Levinsohn, and Pakes (1995) using first-order conditions. The full equilibrium is then simulated under the assumption of no ETFs but with consumer decisions still affected by handset durability.

In the no-ETF equilibrium, assuming that handsets continue to be subsidized, service fees are higher by 2.10 to 5.17 percent, with larger increases for bigger carriers. Consumer surplus is higher by 68 percent so that the lifetime value of the wireless service for consumers increases from 2,347 to 3,932 dollars. Profits from service fees increase by 46 to 89 percent, with smaller carriers gaining more. However, the elimination of ETFs also eliminates revenues received from these payments. If the costs of administering and processing ETFs were zero, then industry profits would in fact be lower without ETFs. However, if processing costs were high enough, e.g., constituting at least 1.60 dollars per month and per subscriber for Verizon, 1.25 dollars for AT&T, 60 cents for Sprint, and less than 50 cents for smaller carriers, then equilibrium profits would be higher without ETFs.

Related literature. In seminal work, Klemperer (1987) showed that switching costs give rise to offsetting pricing incentives: On the one hand, firms want to set low prices to acquire new customers; on the other, they want to exploit locked-in customers by setting high prices. A number of theoretical papers have used an infinite-horizon Hotelling model similar to ours to further explore the investing-harvesting trade-off and derive predictions on the effects of switching costs on price levels (Beggs and Klemperer, 1992; Doganoglu, 2010; Somaini and Einav, 2013; Rhodes, 2014; Fabra and Garcia, 2015). Our stylized theoretical model is closest in spirit to Beggs and Klemperer (1992)'s, in that we also assume that switching costs are

[4]Under open-loop strategies with consumers having perfect foresight, the firms take into account the fact that a change in the price of any product affects the demand for all products in all time periods.

so high that consumers never switch. In contrast to them, we find that equilibrium prices are lower when consumers face switching costs. The reason for this discrepancy is that, in our model, a locked-in consumer pays the price specified in her contract, and not the going market price—a reasonable assumption for the wireless industry. Under this assumption, switching costs reduce the perceived level of product differentiation—an idea that goes back to von Weizsäcker (1984)—thus resulting in lower prices. Importantly and in contrast to those papers, we endogenize the firms' decision whether to impose switching costs.

In the empirical industrial organization literature, the parameters of dynamic models are estimated using either a variant of the two-step method or a full-solution approach. Varrious two-step estimators have been developed following work by Hotz and Miller (1993) and Hotz, Miller, Sanders, and Smith (1994); these include Aguirregabiria and Mira (2002, 2007), Bajari, Benkard, and Levin (2007), Pakes, Ostrovsky, and Berry (2007), and Pesendorfer and Schmidt-Dengler (2008).[5] Such methods typically estimate policy functions in the form of conditional choice probabilities, which are then used to compute value functions. A key limitation of those methods is that they require observing all payoff-relevant variables to obtain consistent estimates of the policy functions.[6] By contrast, there is no such requirement for full-solution techniques, as originally introduced by Rust (1987). Their implementation, often combined with a nested fixed-point algorithm similar to the one in the present paper, is, however, significantly more computationally intensive.

Since a credible model of dynamic consumer behavior typically requires including unobserved state variables, the literature on dynamic demand estimation has relied more on the full-solution approach. Thus, the Markovian framework proposed by Melnikov (2013) and further developed by Gowrisankaran and Rysman (2012) has been used to estimate the demand for durable, storable, or subscription goods in markets with many products. Tractability is achieved by reducing the state space by restricting consumers' beliefs about the evolution of the industry using an *inclusive value sufficiency (IVS)* assumption. The state of the market is thus summarized by a uni-dimensional sufficient statistic, which is assumed to follow a simple autoregressive process. One interpretation is that consumers are boundedly rational, in that they do not fully use the information available to them when forming expectations and making decisions. Examples of papers using the IVS assumption include Hendel and Nevo (2006), Schiraldi (2011), and Nosal (2012). When the number of products is small, the IVS assumption can be relaxed, as in Shcherbakov (2016)'s study of switching costs in the paid-television industry. Using the IVS assumption, Weiergräber (2019) studies the interplay between switching costs and network effects in the US wireless industry using data similar to ours, but abstracting away from consumers' handset choices.

[5] A good review is provided in Aguirregabiria and Nevo (2013).

[6] Arcidiacono and Miller (2011) develop a two-step method that can accommodate unobserved heterogeneity if the dynamic model has the finite-dependence property.

By contrast, we assume that consumers are fully rational, having perfect foresight over the evolution of the industry. Although this assumption rules out uncertainty in consumer beliefs, it endows distinct advantages to the model. First, it allows consumers to account separately for the evolution of the quality of each product; thus, in contrast to Markovian frameworks, a consumer can believe that two products that currently deliver the same flow utility will evolve very differently in the future. We believe this to be important to accurately model the decision process in the wireless market. Second, by using the actual product evolution for each product, we can avoid approximation errors in the estimation of beliefs. With perfect foresight, it is clear that the actual evolution of product characteristics is driving the results. Third, our supply-side model, which assumes firms make pricing decisions under perfect foresight, is consistent with our demand-side approach—whereas, for computational reasons, such consistency is typically not achievable in Markovian frameworks.

The rest of the paper is organized as follows. In Section 2 we develop and solve a simple theoretical model that motivates our empirical analysis. Section 3 describes the data. The dynamic model of consumer demand and estimation algorithm are presented in Section 4. We discuss identification arguments and instrumental variables in Section 5. Estimation results are reported in Section 6. Section 7 introduces the supply-side model and presents our counterfactual simulations. Section 8 concludes.

2 Theoretical predictions

We begin by introducing an illustrative, theoretical model of competition with switching costs. We consider a discrete-time, infinite-horizon, duopoly model. There is a mass 1 of consumers with unit demand. Products are differentiated à la Hotelling: If consumer i consumes firm j's product at time t, she receives a utility flow of $\delta - |x_{it} - \ell_j| - p_{ijt}$, where $\delta > 0$ is gross flow utility, ℓ_j is firm j's location on the Hotelling line ($\ell_1 = 0$ and $\ell_2 = 1$), $x_{it} \in [0, 1]$ is consumer i's type in period t, drawn i.i.d. over time and across consumers from a uniform distribution over $[0, 1]$, and p_{ijt} is the price paid by consumer i to firm j. A consumer that does not consume receives a flow utility of zero, and we assume throughout that δ is sufficiently high so that the market is always covered. Consumers' discount factor is $\beta_c \in (0, 1)$.

The firms are symmetric, their discount factor is $\beta_f \in (0, 1)$, and their constant unit cost of production is normalized to zero. ETFs are modeled in a parsimonious way: If firm j uses ETFs and consumer i buys from that firm at contract price p in period t, then consumer i must buy from that firm at the same price in all subsequent periods. Buying instead from a firm that does not use ETFs involves no subsequent commitment.

At time $t = -1$, firms simultaneously decide whether to use ETFs. Next, the dynamic pricing game starts, with the following timing within each period $t \geq 0$: 1. Firms 1 and

2 simultaneously set p_{1t} and p_{2t}. 2. Consumers' types in period t are drawn and become common knowledge.[7] 3. Consumers who previously bought from a firm using ETFs purchase from the same firm at the price specified in their contract. Consumers who have not yet bought from a firm using ETFs make purchase decisions.

We look for stationary subgame-perfect equilibria in pure strategies, with stationarity being defined as follows: For a given action profile in stage $t = -1$, firm j sets the same price in all subgames of the dynamic pricing game. This restriction rules out collusive equilibria based on rewards and punishments.

We use backward induction, solving first for equilibria in each of the subgames starting at time 0. Consider the subgame in which no firm uses ETFs. Since buying from either firm involves no subsequent commitment, purchase and pricing decisions are static. As in standard Hotelling, the location of the marginal buyer at time t, $\hat{x}_t$, solves the indifference condition

$$\delta - p_{1t} - \hat{x}_t = \delta - p_{2t} - (1 - \hat{x}_t), \tag{1}$$

which gives $\hat{x}_t = 1/2 + (p_{2t} - p_{1t})/2$. Hence, in the unique stationary equilibrium, firms set the standard Hotelling equilibrium prices $p_1 = p_2 = 1$. Each firm makes a per-period profit of 1/2, and, integrating over consumers' types, per-period consumer surplus is $\delta - \frac{5}{4}$.

Next, we turn to the subgame in which both firms use ETFs. Consider buyer i at time t, and suppose that buyer has not yet purchased from either firm. (Buyers who purchased from one of the firms have no decision to make.) If consumer i buys from firm j, she receives

$$\delta - p_{jt} - (1 - \beta_c)|x_{it} - \ell_j| - \beta_c \frac{1}{2},$$

where $|x_{it} - \ell_j|$ is current transport costs, 1/2 is future (expected) transport costs, and we have converted intertemporal payoffs into flow payoffs by pre-multiplying by $1 - \beta_c$. The location of the marginal buyer, $\tilde{x}_t$, is thus pinned down by the indifference condition

$$\delta - p_{1t} - (1 - \beta_c)\tilde{x}_t = \delta - p_{2t} - (1 - \beta_c)(1 - \tilde{x}_t). \tag{2}$$

We thus obtain $\tilde{x}_t = 1/2 + (p_{2t} - p_{1t})/(2(1 - \beta_c))$, which means that consumers behave as in a Hotelling model with transport cost parameter $1 - \beta_c$. Given this behavior, it is easily shown that firms set the corresponding Hotelling equilibrium prices, $p_1 = p_2 = 1 - \beta_c$, and each firm makes a per-period profit of $(1 - \beta_c)/2$. Expected consumer surplus is $\delta - \left(\frac{5}{4} - \beta_c\right)$ in period $t = 0$, and $\delta - \left(\frac{3}{2} - \beta_c\right)$ in all subsequent periods.

[7] The assumption that types are publicly observed is innocuous. It allows us to use subgame-perfect equilibrium as our solution concept. The equilibrium outcome would be the same if we assumed instead that types are private information and solved for (stationary) perfect Bayesian equilibria.

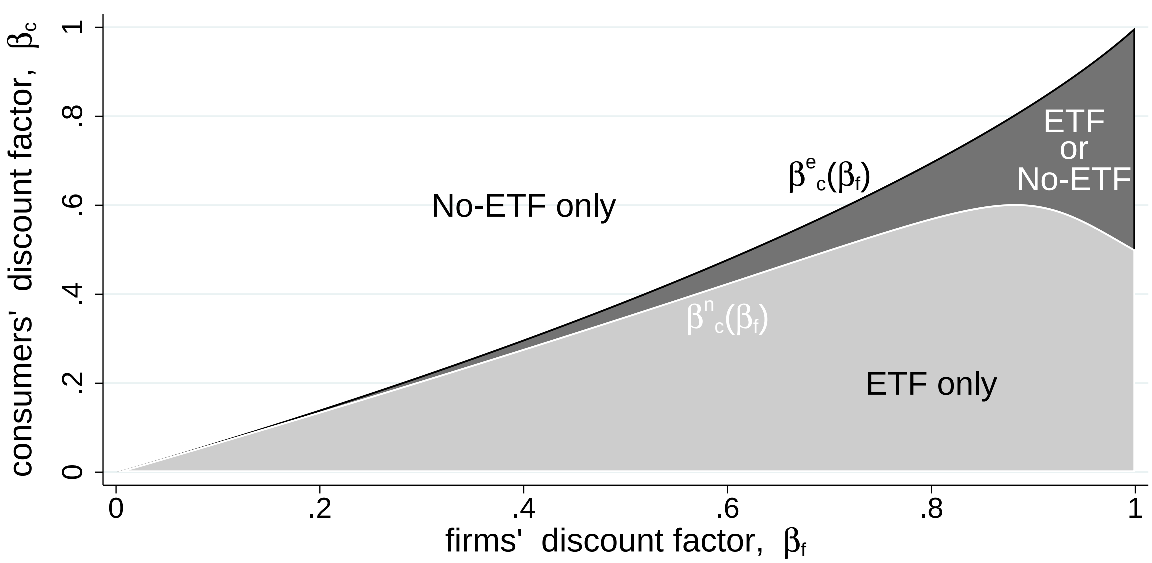
Subgames in which one firm uses ETFs and the other one does not are more complex. Since, as shown below, they are always off the equilibrium path, we relegate their equilibrium analysis to Appendix A.1. We have:

Proposition 1. *Asymmetric outcomes in which one firm uses ETFs and the other one does not never arise in equilibrium. Moreover, for every β_f, there exist cutoffs $\beta_c^n(\beta_f) < \beta_c^e(\beta_f)$ such that: No firm using ETFs is an equilibrium if and only if $\beta_c \geq \beta_c^n(\beta_f)$; and both firms using ETFs is an equilibrium if and only if $\beta_c \leq \beta_c^e(\beta_f)$.*

Proof. See Appendix A.2. □

Thus, the equilibrium depends on the relative patience of consumers and firms. Figure 1 provides a graphical representation of Proposition 1 in the (β_f, β_c) plane. The lightly shaded area shows the range of parameters where both firms using ETFs is the only equilibrium—there, imposing ETF is a dominant strategy. This occurs provided firms are much more patient than consumers. Instead, in the unshaded area consumers are more patient than producers, so that ETFs are not used in the unique equilibrium. In the darkly shaded area, there are two equilibria: Either both firms impose an ETF or neither firm does. The range of discount factors where this occurs is economically relevant: To the extent that consumers can be expected to be less patient or forward-looking than firms (and yet not completely myopic either), multiple equilibria are likely to exist, so that firms face a coordination problem.

Figure 1: Equilibrium characterization



Importantly, firms and consumers are not indifferent between the two equilibria. To understand this, we begin by comparing equilibrium prices, which are equal to $1 - \beta_c$ when

ETFs are used and to 1 when they are not. Thus, firms price more aggressively in the ETF equilibrium. Intuitively, with ETFs, a consumer that chooses between firms 1 and 2 views the two firms as differentiated in the current period (since the consumer knows her current type), but as homogeneous in expectation in subsequent periods (since the consumer's type will be independently redrawn). Since the consumer puts a weight of $1-\beta_c$ (resp. β_c) on her current (resp. future) payoffs, this results in a perceived transport cost parameter of $1-\beta_c$ in equation (2). By contrast, without ETFs, purchasing from a given firm at time t involves no subsequent commitments. The consumer therefore puts full weight on current-period payoffs, which results in a transport cost parameter of 1 in equation (1). As consumers perceive firms to be less differentiated when ETFs are used, the resulting equilibrium prices are lower.

In this simple model, it is clear that firms prefer the no-ETF equilibrium since they set higher prices in that equilibrium and receive a market share of 1/2 regardless of which equilibrium is selected. When it comes to consumers, the comparison is *a priori* less clear: In the ETF equilibrium, buyers benefit from lower prices but suffer from being unable to switch. It turns out that the latter effect dominates, so that consumers are better off with ETFs.[8]

This stylized model delivers some important takeaways. First, the observation that firms use ETFs does not necessarily imply that they would not be better off coordinating on not using them. The use of ETFs is an equilibrium phenomenon and there is no reason to expect it to be a dominant strategy for firms. Second, when ETFs are used, firms compete more fiercely to lock in consumers, and prices thus tend to be lower. Third, while consumers are locked in when ETFs are imposed, they may in fact benefit from lower equilibrium prices.

Some of the predictions of this stylized model should not be taken too literally, however. The result that firms are *always* worse off in the ETF equilibrium seems to rely strongly on the assumption that consumers can never switch, and so firms never receive ETF payments. Similarly, the result that consumers are *always* better off with ETFs is driven by the fact that the gap between ETF and no-ETF prices is substantial. As explained above, such a large gap arises because consumers do not know their future types and thus perceive the two firms' products as homogeneous in expectation. One may expect this gap to shrink if it is the case that a consumer that prefers product j to product k today is likely to have the same preferences in the future. In the remainder of the paper, we develop and estimate a structural model that addresses these and related shortcomings, and use it to provide a credible quantitative assessment of the welfare effects of early termination fees.

[8]This holds since per-period consumer surplus is $\delta - 5/4$ without ETFs, whereas, with ETFs, it is

$$(1-\beta_c)\left[\delta - \left(\frac{5}{4} - \beta_c\right)\right] + \beta_c(1-\beta_c)\left[\delta - \left(\frac{3}{2} - \beta_c\right)\right] = \delta - \frac{5}{4} + \frac{3}{4}\beta_c.$$

3 Data

We use data from a quarterly cross-sectional consumer survey collected by *Comscore Inc.* from 2005 to 2012. *Comscore* administers the detailed survey to a random sample of approximately 36,000 cell phone users each quarter to quantify market growth and cell phone usage patterns. The survey includes questions on handset used, price paid for the handset, current carrier, monthly fee for the calling plan, demographic characteristics of the individual, etc. In addition, *Comscore* maintains a database of detailed handset characteristics that can be matched to the cell phone model owned by an individual. The sample of consumers is weighted and balanced to match national subscriber numbers and demographic characteristics.

The major wireless operators are Verizon, AT&T, T-Mobile, and Sprint, all of which offer virtually nationwide service. We aggregate other regional or local wireless carriers into a separate category labeled "Other".[9] The top four carriers account for the vast majority of cell phone users; approximately 90% of the users in the sample subscribed with one of them.

Our product definition is a handset-carrier combination. For example, we define the iPhone 4S on the AT&T network as a product and calculate its market share for each year as the total number of subscribers divided by the US population. The total market share of the carrier is simply the sum of the market shares of each of its products. Figure 2 shows the evolution of those market shares over the course of the sample. On average, carrier market shares have increased over time as cell phones have become increasingly common. Note that those aggregate shares mask the rich variation in handset-carrier market shares; the latter facilitates identification in our model.

The survey also includes information on monthly service fees and, for those who purchased a phone in the current month, the price they paid for their handset. For the price of the handset market, we use the average reported handset price by individuals in that year. For the carrier monthly fee, we use the average monthly fee for all subscribers to that carrier.[10] Figure 3 illustrates the evolution of average handset prices (left panel) and service fees (right panel) as reported by the survey participants.

[9] There have been a few significant mergers in the industry. The largest was the merger of Cingular and AT&T, which occurred before the beginning of our sample. A smaller merger occurred in 2009 when Verizon acquired Alltel wireless, the fifth largest wireless company at the time. The data provided by Comscore retroactively aggregated the market shares of Alltel and Verizon together for the whole sample.

[10] We observe only expenditures, and not the exact characteristics of the service plans. In the estimation, we therefore assume that all wireless subscribers choose the same service plan. This is not innocuous because the same model of handsets can be offered with very different plans (e.g., large data plan, family plan, etc.).

Figure 2: Market share by carrier-year, 2005-2012

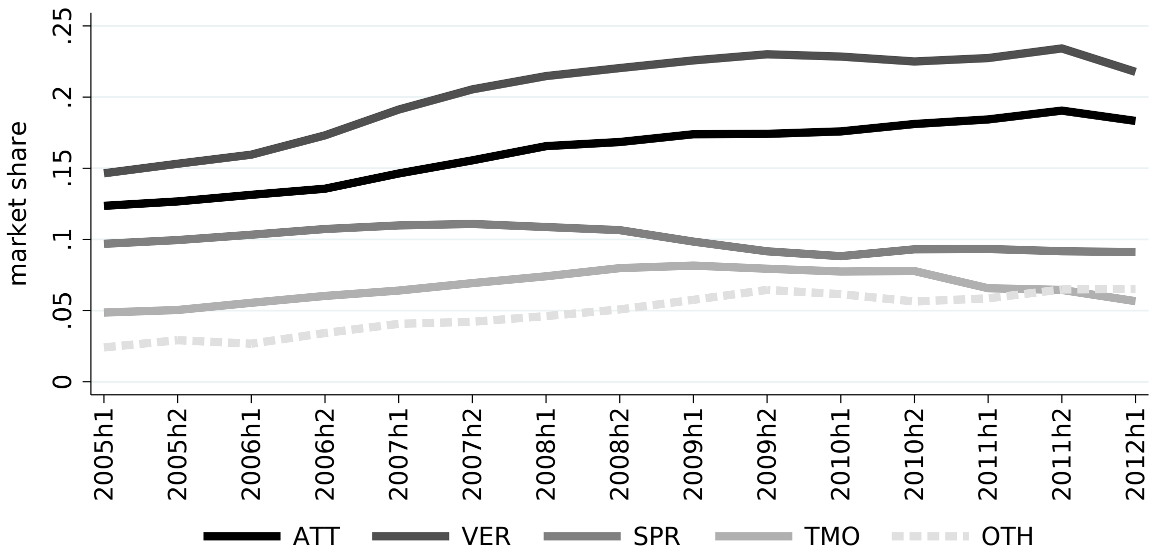
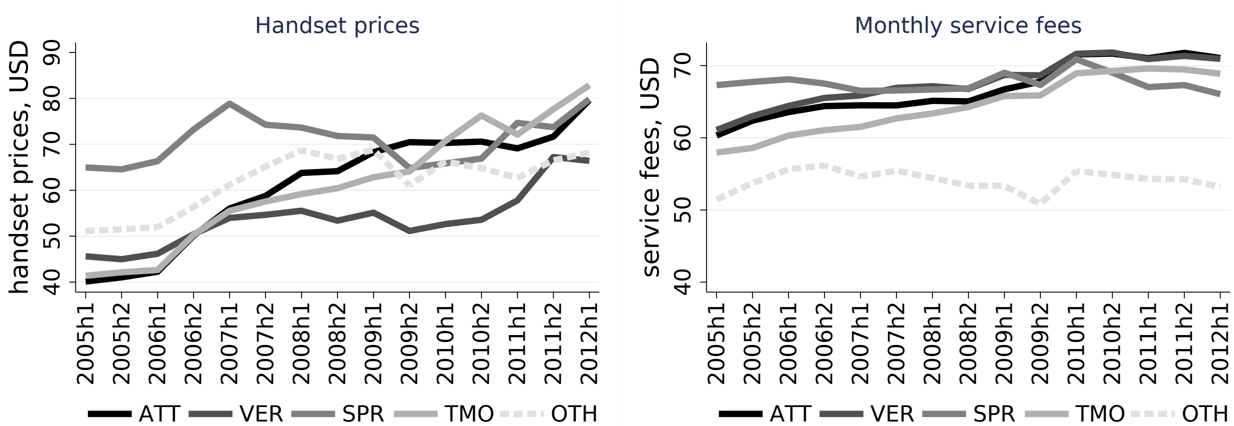


Figure 3: Average handset prices (left) and service fees (right) by carrier-year, 2005-2012



Notes: Reported handset prices are weighted by the number of respondents.

Since handsets are durable, the number of possible handsets on each carrier increases over time as new handsets are introduced; when estimating the structural model, we assume that any handset available in earlier years could be used in later periods. It is worth noting that the survey may not contain information on market shares for all possible handset-carrier combinations. Therefore, while our model will predict the entire distribution of shares, to form moment conditions we match the model predictions only to the observations available from the survey. Figure 4 summarizes the average number of distinct handset models used with each of the main wireless service providers.

Figure 4: Number of handsets by carrier-year, 2005-2012

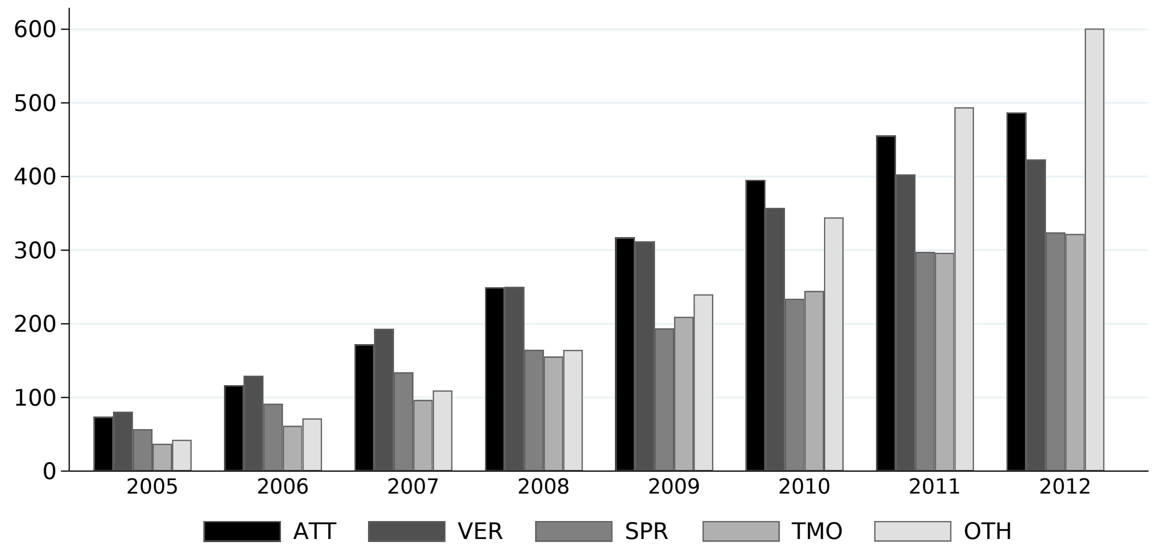


Table 1 lists some of the handset characteristics available in our data. Although we estimate our dynamic model using handset dummy variables, those characteristics are used to construct instrumental variables based on product "similarity" (see Section 5).

To estimate our model, we aggregate quarterly data to the bi-annual level. The aggregation is used to obtain more precise measures of market shares at the handset-carrier-time level. As our estimation algorithm relies on a dynamic version of the inversion method originally proposed by Berry, Levinsohn, and Pakes (1995), an accurate measure of population purchase probabilities is important for the consistency of our estimates.

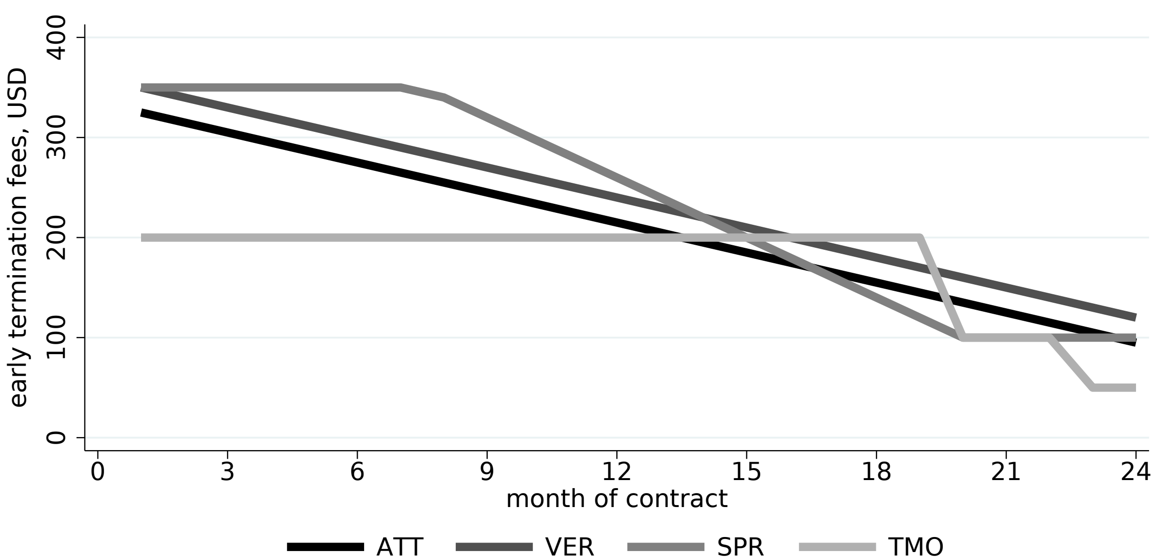
We collect data on early termination fees from carrier websites and past announcements. The ETF schedules are generally fixed for years at a time. We only observe one revision of ETFs for each carrier over the sample. The shift seems to be motivated primarily by the cost of smart phones: Over the 2009-2011 time period, each carrier introduced a higher ETF for such "advanced devices", which generally enjoyed a higher carrier subsidy. Even though advanced ETFs are much larger, the percentage decline over the lifetime of the contract is very similar to the ETFs for basic devices. Figure 5 shows the ETFs for advanced devices for each month of a two-year service contract.

Table 1: Selected handset characteristics

variable name	variable name
Smartphone (y/n)	GPS (y/n)
Built-in storage (y/n)	Email (y/n)
Java version (MIDP 2.0, Dalvik, etc.)	Full-keyboard (y/n)
Bluetooth (y/n)	GPRS (y/n)
Infrared (y/n)	IM (y/n)
Display width	MMS (y/n)
Display height	MPEG-4 (y/n)
Display color (65,536; B&W, etc.)	Formfactor (Candybar, Slider, etc.)
Audio type (realtones, monophonic, etc.)	Release date (year/q)
GSM (y/n)	OS type (Microsoft, Symbian, etc.)
CDMA (y/n)	Camera resolution (mgp)

Notes: GSM stands for global system for mobile communications; CDMA for code-division multiple access; GPS for global positioning system; GPRS for general packet radio services; IM for instant message; MMS for multimedia messaging service; and MPEG for moving picture experts group standards.

Figure 5: Early termination fees for advanced devices by carrier



4 Dynamic demand

4.1 Consumer behavior

Time is discrete and corresponds to a six-month interval, consistent with the data we use for estimation. Products are defined as handset-carrier combinations. The set of products in each time period t is denoted $\mathcal{J}'_t \subseteq \mathcal{H}_t \times \mathcal{C}$, where $\mathcal{C}$ is the set of wireless service providers and $\mathcal{H}_t$ the set of handsets available in period t. To this set, we add the outside option of not using contract-based wireless communication services, and define $\mathcal{J}_t = \mathcal{J}'_t \cup \{o\}$. The cardinality of $\mathcal{J}_t$ is denoted J_t. We assume that a product that is available in period t remains available in all subsequent periods, i.e., $\mathcal{J}_t \subseteq \mathcal{J}_{t'}$ whenever $t' \geq t$. Handsets are durable and do not depreciate. We assume that consumers cannot choose a different service provider without buying a new handset.[11]

There is a finite number of consumer types, $i = 1, \ldots, N$, characterized by a price sensitivity parameter α_p^i. Contracts have a duration of two years, denoted as $\mathcal{T} = 4$ periods. At the beginning of each period, a consumer decides whether to sign a contract or continue with the current contract. Premature termination of a contract is costly. Let $d_t^i \in \mathcal{J}_t \cup \{\varnothing\}$ denote the consumer's purchase decision. Note that the set of available actions contains the possibility of not making an active purchase decision (i.e., not signing a new contract, but rather staying on the same contract as in the previous period), in which case $d_t^i = \varnothing$.

At the beginning of each period t, each consumer is endowed with current holding $e = (j, \tau) \in \bigcup_{t'=0}^{t-1} \mathcal{J}_{t'} \times \{t'\}$, where j denotes the product that the consumer currently holds (which can be the outside option) and τ the period when that product was purchased. For example, a consumer can be endowed with an *iPhone 4* purchased under a contract with *AT&T* on May 9, 2011, which we denote as $e = (\textit{iPhone 4 with AT\&T}, 05/09/2011)$. When a new product is purchased, the old endowment is disposed of at no cost. The per-period utility flows of a holding may evolve over time (for example, due to changes in service quality).

Since $\tau \leq t$ records the time of the most recent purchase, $t - \tau$ determines the age of the consumer endowment. Thus, (e, t) completely describes the age and value of any endowment at the beginning of each period. There are three types of payments that consumers may make in period t. A consumer who is currently endowed with e pays a service fee p_e to her service provider—the fact that p_e does not depend on t means that those fees are specified at the beginning of the contract (period τ if $e = (j, \tau)$) and stay constant over time unless the contract is terminated. Moreover, a consumer who makes an active purchase decision, switching from holding e to holding (d, t), must pay an early termination fee of F_{et} to her previous service provider, as well as the price of her new handset P_{dt} to her new wireless carrier. The ETF schedule satisfies $F_{et} > 0$ if $t - \tau < \mathcal{T}$ and $F_{et} = 0$ otherwise. We set all

[11] This is true for the early years of our data but may be restrictive for the most recent years.

payments to the outside option equal to zero, i.e., $p_{o\tau} = F_{o\tau t} = P_{ot} = 0$.

Consider a consumer of type i who starts period t with holding $e = (j, \tau)$. If the consumer does not make an active purchase and thus keeps that holding, she receives a utility flow of

$$\delta_{jt} - \alpha_p^i p_e + \varepsilon_{\varnothing t}^i,$$

where δ_{jt} denotes the mean flow utility (gross of payments to the service provider) of product j in period t, and $\varepsilon_{\varnothing t}^i$ is an idiosyncratic match value. If instead she makes an active decision and purchases a product $d \in \mathcal{J}_t$, then her holding becomes (d, t) and she receives

$$\delta_{dt} - \alpha_p^i \left(p_{dt} + F_{et} + P_{dt}\right) + \varepsilon_{dt}^i$$

in the current period.[12] The ε shocks are drawn i.i.d. from a standard Gumbel distribution.

Consumers maximize the expected present discounted value of utility flows, having perfect foresight over future product attributes, except for future ε draws. The state variables for the consumer dynamic programming problem are: the consumer endowment, $e = (j, \tau)$; the current time period, t; and the vector of idiosyncratic shocks in the current period, $\boldsymbol{\varepsilon}$. The dynamic problem can thus be formulated recursively with the Bellman equation

$$V^i(e, t, \boldsymbol{\varepsilon}) = \max \left\{ \begin{array}{c} \delta_{jt} - \alpha_p^i p_e + \varepsilon_{\varnothing t}^i + \beta V^i(e, t+1), \\ \max\limits_{d \in \mathcal{J}_t} \left[\delta_{dt} - \alpha_p^i \left(p_{dt} + F_{et} + P_{dt}\right) + \varepsilon_{dt}^i + \beta V^i((d, t), t+1)\right] \end{array} \right\}, \tag{3}$$

where $V^i((d, \tau), t) \equiv \mathbb{E} V^i((d, \tau), t, \boldsymbol{\varepsilon})$.

Taking expectations in the Bellman equation and applying standard properties of the Gumbel distribution, we obtain a recursive formula for $V^i(e, t)$:

$$V^i(e, t) = \log \left[\begin{array}{c} \exp\left(\delta_{jt} - \alpha_p^i p_e + \beta V^i(e, t')\right) \\ + \exp\left(\delta_{dt} - \alpha_p^i \left(p_{dt} + F_{et} + P_{dt}\right) + \beta V^i((d, t), t')\right) \end{array} \right]. \tag{4}$$

Mean flow utilities. For all periods in our sample, $t = 1, \ldots, T$, we assume that, for product j, which consists of handset h sold by carrier c, the mean flow utility δ_{jt} is

$$\delta_{jt} = \alpha_0 + \alpha_h + \alpha_t^c + \xi_{jt}, \tag{5}$$

where α_h is a handset fixed effect, α_t^c a carrier-time fixed effect, and ξ_{jt} a product-specific mean-zero innovation. The mean flow utility of the outside option is normalized to zero.

[12] In principle, d could be equal to j, meaning that we allow for repeated purchases of the same product.

Initial conditions and terminal-period beliefs. The first period of our data is $t = 1$ and we have no information on consumer holdings prior to that. We assume that $\mathcal{J}_0 = \{o\}$, which means that all consumers initially hold the outside option.

We assume that after the terminal period in our data, T, and until period $T' = T + 60$, consumers believe that the flow utility of each product evolves over time according to the deterministic process

$$\delta_{jt} = \hat{\gamma}_0^c + \hat{\gamma}_1^c \delta_{jt-1}, \tag{6}$$

where c denotes carrier identity, and $\hat{\gamma}_0^c$ and $\hat{\gamma}_1^c$ are parameter estimates from the AR(1) OLS regression

$$\delta_{j\tau} = \gamma_0^c + \gamma_1^c \delta_{j\tau-1} + \nu_{j\tau},\ j \in \mathcal{J}_\tau,\ \tau = 1, \ldots, T.$$

Consumers also believe that handset prices and service fee evolve according to auto-regressive specifications analogous to equation (6).[13] Schedules of ETFs are assumed to remain the same for all periods after T. Finally, after period T', the market disappears and consumers no longer receive any utility, nor do they make any payments.[14]

To solve the dynamic programming problem for consumer type i for a given vector of mean flow utilities, we proceed as follows. First, we augment our data with 60 periods after the terminal period T, as described above. We can then solve the consumer problem by using a backward-induction algorithm starting with the final period (period $T' + 1$) with rewards equal to zero, and then folding backwards using equation (4). It is clear that we never observe the δ_{jt}s in the data. However, we observe consumer purchase decisions, which can be mapped into mean flow utilities as we describe in the next subsections.

4.2 Computing market shares

Our estimation algorithm uses data on product-level market shares, which we now define. Let s_{jt} (resp. s_{jt}^i) denote the aggregate market share (resp. the observed market share in consumer group i) for a particular handset-carrier combination j at time t. Note that current-period purchase decisions depend on current holdings, which are determined by the consumers' decisions in previous periods. This means that, to determine purchase probabilities and thus

[13] As mentioned in the introduction, similar assumptions on the evolution of consumer beliefs are commonly used in the literature on dynamic demand estimation (e.g., Schiraldi, 2011; Gowrisankaran and Rysman, 2012; Shcherbakov, 2016; Weiergräber, 2019). In contrast to that literature, we make this assumption at the product level and only for the time periods that are beyond those in our sample. For all periods in our sample, consumer beliefs are pinned down by the *actual* evolution of payoff-relevant variables.

[14] For computational reasons, we assume that the number of products stays constant after period T. We experimented with shorter and longer time spans left after the terminal data period and found no difference in parameter estimates for all models extended by 60 time periods (i.e., 30 years) or more forward. There are only minor differences in parameters estimated using models extended by 30 and 60 periods forward. See Section 6 for further robustness checks on initial conditions and terminal-period beliefs.

market shares for any product at time t, we need to circle over all possible holdings, and thus all products that were ever available in the market up to the current time period.

Formally, consider the conditional probability that consumer type i actively purchases product $d \in \mathcal{J}_t$ in period t, given that her current holding is $e = (j, \tau)$. This probability, denoted $\Pr^i(d|e,t)$, is given by:

$$\mathbb{P}\begin{pmatrix} \delta_{dt} - C^i_{edt} + \beta V^i\left((d,t),t+1\right) + \varepsilon^i_{dt} \geq \delta_{jt} - \alpha^i_p p_e + \beta V^i\left(e,t+1\right) + \varepsilon^i_{\varnothing t}, \\ \delta_{dt} - C^i_{edt} + \beta V^i\left((d,t),t+1\right) + \varepsilon^i_{dt} \geq \delta_{kt} - C^i_{ekt} + \beta V^i\left((k,t),t+1\right) + \varepsilon^i_{kt},\ \forall k \in \mathcal{J}_t \end{pmatrix}$$
$$= \frac{\exp\left(\delta_{dt} - C^i_{edt} + \beta V^i\left((d,t),t+1\right)\right)}{\exp\left(\delta_{jt} - \alpha^i_p p_e + \beta V^i\left(e,t+1\right)\right) + \sum_{k\in\mathcal{J}_t}\exp\left(\delta_{kt} - C^i_{ekt} + \beta V^i\left((k,t),t+1\right)\right)},$$

where $C^i_{ekt} \equiv \alpha^i_p\left(p_{kt} + F_{et} + P_{kt}\right)$. If product d is not yet available (i.e., $d \notin \mathcal{J}_t$), then $\Pr^i(d|e,t) = 0$.

To compute current-period product shares for each consumer type i, we define a matrix of current consumer holdings, $\boldsymbol{\sigma^i[t]}$. That matrix has dimension $J_T \times (t+1)$, where J_T is the number of products available in period T.[15] A generic element of matrix $\boldsymbol{\sigma^i[t]}$ is denoted $\sigma^i_{j\tau}[t]$, the share of type-i consumers with holding $(j,\tau) \in \mathcal{J}_T \times \{0,1,\ldots,t\}$ at the end of period t. We construct $\boldsymbol{\sigma^i[t]}$ by induction on t. As all consumers hold the outside option at the beginning of the first period by assumption, we set $\sigma^i_{o0}[0] = 1$ and $\sigma^i_{j0}[0] = 0$ for every $j \neq o$, which defines $\boldsymbol{\sigma^i[0]}$. Having constructed $\boldsymbol{\sigma^i[0]}, \ldots, \boldsymbol{\sigma^i[t-1]}$, we can then define $\boldsymbol{\sigma^i[t]}$ as follows: For every $j \in \mathcal{J}_T$

$$\sigma^i_{jt}[t] = \sum_{e\in\bigcup_{t'=0}^{t-1}\mathcal{J}_{t'}\times\{t'\}} \Pr^i(j|e,t)\sigma^i_e[t-1], \tag{7}$$

and for every $\tau \in \{0,1,\ldots,t-1\}$,

$$\sigma^i_{j\tau}[t] = \sigma^i_{j\tau}[t-1]\left(1 - \sum_{k\in\mathcal{J}_T}\Pr^i(k|(j,\tau),t)\right). \tag{8}$$

Equation (7) gives the share of consumers who actively purchased product j in period t, and are thus endowed with (j,t) at the end of that period. Equation (8) gives the share of consumers who started period t with holding (j,τ), did not make an active purchase decision in that period, and thus ended the period with the same holding. (Note that the above formulas imply that $\sigma^i_{j\tau}[t] = 0$ if $j \notin \mathcal{J}_\tau$.)

Having constructed those holdings matrices, we can simply compute s^i_{jt} by adding up the

[15] As $\mathcal{J}_T$ contains $\mathcal{J}_t$ for every t, J_T is also the total number of products that will ever be available.

shares of type-i consumers holding product j at the end of the period:

$$s^i_{jt} = \sum_{\tau=0}^{t} \sigma^i_{j\tau}[t]. \tag{9}$$

Finally, the aggregate market share of product j is computed as the weighted sum of product shares for all consumer types:

$$s_{jt} = \sum_{i=1}^{N} w^i_t \, s^i_{jt}, \tag{10}$$

where w^i_t is the weight of consumer type i in the population.

4.3 Mean flow utility and estimation algorithm

The main objective of our estimation algorithm is to recover the structural parameters α^i_p, α_0, α_h, and α^c_t. Our model predicts aggregate market shares as a function of $\boldsymbol{\delta} = ((\delta_{k\tau})_{k\in\mathcal{J}_\tau})_{1\le\tau\le T}$ for any given vector of price sensitivities $\boldsymbol{\alpha_p} = (\alpha^1_p, \dots, \alpha^N_p)$. Let $\widehat{s}_{jt}(\boldsymbol{\delta}, \boldsymbol{\alpha_p})$ be the predicted market share of product j at time t.

Our first step is to recover $\boldsymbol{\delta}$, which can be done by solving the system of equations

$$s_{jt} = \widehat{s}_{jt}\left(\boldsymbol{\delta}, \boldsymbol{\alpha_p}\right), \quad \forall t \in \{1, \dots, T\}, \ \forall j \in \mathcal{J}_t, \tag{11}$$

where s_{jt} is the market share observed in the data. We employ an inversion algorithm similar to Berry, Levinsohn, and Pakes (1995). We begin with arbitrary starting values for $\boldsymbol{\delta}$ and estimate $(\hat{\gamma}_{0,c}, \hat{\gamma}_{1,c})$ (see equation (6)), as well as two similar regressions for handset prices and service fees. Next, we fill in the extended data set for all periods and products beyond the observed terminal period T and solve the consumer dynamic programming problem by backward induction, as explained in Section 4.1. The solution to the consumer problem is then used to compute the predicted market shares $\widehat{s}_{jt}(\boldsymbol{\delta}, \boldsymbol{\alpha_p})$ (see Section 4.2). We then update the mean flow utilities as follows:

$$\delta^{(\ell+1)}_{jt} = \delta^{(\ell)}_{jt} + \log s_{jt} - \log \hat{s}_{jt}\left(\boldsymbol{\delta}, \boldsymbol{\alpha_p}\right),$$

where $\delta^{(\ell)}_{jt}$ and $\delta^{f(\ell+1)}_{jt}$ are the current and the next iteration values of the mean flow utility of product j at time t. We keep iterating until value functions from two consecutive iterations are close enough.

To estimate structural parameters, we use a nested fixed-point algorithm. The inner loop recovers mean flow utilities for a given vector $\boldsymbol{\alpha_p}$, as described above. Having done this, we use those mean utilities to estimate equation (5), which gives us estimates for the linear parameters α_0, α_h, and α_t^c. We can then net out unobserved product characteristics and form moment conditions for estimating the non-linear parameters α_p^i. Those moment conditions are constructed under the assumption that the product-specific innovations ξ_{jt} satisfy $\mathbb{E}[\xi_{jt}|Z_{jt}] = 0$, where Z_{jt} is a vector of instruments discussed in detail in Section 5. The outer loop searches for nonlinear parameter values by employing the Nelder-Mead simplex method to minimize the resulting generalized method of moments (GMM) objective function.

In the version of the model with consumer heterogeneity, the identification of type-specific price coefficients is facilitated by including micro-moment conditions based on the difference between observed type-specific purchase probabilities (s_{jt}^i) and model predictions ($\widehat{s}_{jt}^i$; see equation (9)). These additional moment conditions are defined using the mean-zero residual

$$\nu_{jt}^i = s_{jt}^i - \widehat{s}_{jt}^i, \tag{12}$$

which represents approximation errors.[16] The only instrumental variable we use for the micro-moments is a constant term. To construct the GMM objective function, we stack moments based on ξ and ν and employ a block-diagonal weighting matrix. The weighting matrix for the first-stage GMM is calculated as $(Z'Z)^{-1}$, while the second-stage optimal weighting matrix is based on the inverse covariance matrix of the individual moment conditions.

5 Instruments and identification

It is conceivable that wireless service providers observe ξ_{jt} (at least partially) prior to choosing their service fees, p_e, and handset prices, P_{jt}. We are less concerned with the early termination fees, as they are typically identical for a wide range of products and change very infrequently.

To address the endogeneity problem, we construct several instrumental variables similar to Berry, Levinsohn, and Pakes (1995). We do not observe any provider-specific characteristics except for the identity of the carrier. By using carrier-time effects we control for the nation-wide quality of each carrier's service at any given time period. For handsets, we observe very detailed information as discussed in Section 3. Our instrumental variables measure the intensity of competition facing each of the products as the number and average characteristics of similar handsets offered by competitors. A larger number of substitutes as well as their closer proximity in the characteristics space should negatively affect price-cost margins.

Handset similarity is defined based on whether a given handset is a smartphone, availability of camera, type of OS vendor, handset form factor, and the total number of observable features (e.g., GPS capabilities, radio, Bluetooth, Java, built-in storage, wifi data access). We construct

[16]The identification of preference-heterogeneity parameters using additional micro-level data is discussed in Petrin (2002) and Berry, Levinsohn, and Pakes (2004).

four instrumental variables. The first variable is the number of similar handsets currently offered by competing carriers. The second is the average (across rival products) age of similar handsets as measured by the number of months since the introduction of the product. The third is the average self-reported consumer satisfaction for similar rival products. The fourth is the total number of handsets brought to the market by the same original equipment manufacturer (OEM) in a given time period.

Identification of parameters in our model is based on several assumptions. First, we assume that all consumers discount the future at the same rate of $\beta = 0.95$.[17] Second, our specification of mean population utility from a handset-carrier combination assumes that all consumer types have identical preferences for the attributes of handsets and carriers. In other words, there are no random coefficients on handset and carrier-time dummies. The identification of each consumer type's price sensitivity relies on micro-moments.

One important question is whether the mapping from mean flow utilities to market shares is one-to-one. Similar to Gowrisankaran and Rysman (2012), we allow for repeated consumer purchases over time. Therefore, while the information structure of our problem is similar to Berry, Levinsohn, and Pakes (1995), consumers may choose to buy multiple products over time, and some products may be complements across periods. This prevents us from using the uniqueness proof in Berry (1994). We thus proceed by assuming uniqueness of the vector of mean flow utilities that makes observed market shares equal to the model predictions. Extensive testing reveals that for all trial parameter values and all initial starting values for the mean-flow utility vector, the algorithm always converges to the same solution.

6 Estimation results

We begin by presenting results from static discrete-choice specifications. The main purpose of these regressions is to illustrate the effects of instrumental variables on parameter estimates. Next, we estimate versions of our structural model with and without consumer heterogeneity.

Static model results. In Table 2, we report estimation results for several specifications of a simple static model in which consumers decide every period whether to purchase one of the products or to take the outside option. Every time a consumer purchases a product, she pays the handset price and service fee. Early termination fees are not used in estimation. The mean utility from each handset-carrier combination is obtained as in Berry (1994). Specifications (1), (3), and (5) report OLS estimates. Specifications (2), (4), and (6) report

[17] The identification of the discount factor in dynamic models is known to be a hard problem; see Manski (1993), Rust (1994), Magnac and Thesmar (2002), and Pesendorfer and Schmidt-Dengler (2008) for non-identification results.

estimates from instrumental variable regressions. Results reported in (1) and (2) allow the coefficients on handset price and service fee to differ, while the estimates listed in columns (3)–(6) restrict coefficients on both monetary variables to be the same. We control for product and carrier-time fixed effects or handset and carrier-time fixed effects. The bottom part of Table 2 reports F-statistics from the first-stage regressions in the IV specifications.[18]

Table 2: Results from static model specifications: OLS vs. IV, 16,408 observations

parameters	unrestricted		restricted			
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
handset price, P_{jt}	-4.591	-15.565				
(s.e.)	(0.262)	(14.890)				
service fee, p_{jt}	1.021	-17.273				
(s.e.)	(0.091)	(4.345)				
total cost, $p_{jt} + P_{jt}$			0.340	-17.190	0.755	-9.574
(s.e.)			(0.085)	(4.296)	(0.094)	(2.846)
constant	-8.070	1.702	-8.148	1.787	-3.640	1.368
(s.e.)	(0.046)	(2.216)	(0.046)	(2.092)	(0.173)	(1.396)
product fixed effect	yes	yes	yes	yes	no	no
carrier-time fixed effect	yes	yes	yes	yes	yes	yes
handset fixed effect	no	no	no	no	yes	yes
first-stage statistics						
F statistic, P_{jt}		11.76				
(p-value)		(0.000)				
F statistic, p_{jt}		14.34				
(p-value)		(0.000)				
F statistic, $P_{jt} + p_{jt}$				18.61		6.58
(p-value)				(0.000)		(0.000)

Notes: The total cost variable is the sum of handset price and service fee; instrumental variables include the average number, average age, and average consumer satisfaction for similar products offered by rival carriers as well as the number of handsets introduced by the same OEM in the current period.

Table 2 suggests that the handset price, service fee, and total cost variables are endogenous, as OLS specifications estimate positive coefficients on the latter two variables. IV regressions deliver negative price-coefficient estimates, as expected. Given the endogeneity concerns, we use similar instrumental variables to form moment conditions in the estimation of the dynamic structural model.

Structural model results. All results are second-stage optimal GMM parameter estimates. Table 3 summarizes estimation results from a version of the structural model without consumer heterogeneity (column 2).[19] The instrumental variables used in our main specification are the

[18]Estimation results for the static model using alternative combinations of fixed effects and alternative instrumental variables can be found in Appendix B.1 (Tables 14 and 15).

[19]See Appendix B.2 for summary statistics on carrier-time dummies.

average age and average consumer satisfaction for similar products offered by rival carriers—see below for results using alternative sets of instruments. For convenience of comparison, we also reproduced estimation results from a similar static model (column 1). The bottom part of the table reports summary statistics for the aggregate price elasticity of demand. The last row presents results from the appropriate version of the overidentifying restrictions test. Neither the static nor the dynamic model can be rejected at a reasonable significance level.

Table 3: Second-stage optimal GMM parameter estimates and elasticity predictions

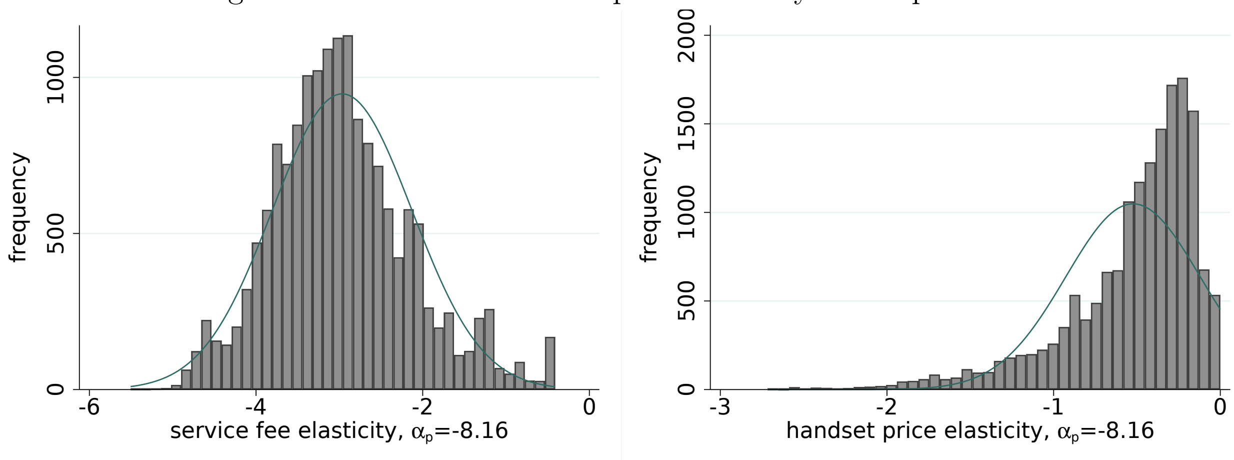
parameter	parameter estimates	
	(1) static	(2) dynamic
price coefficient, α_p	-9.121	-8.163
(s.e.)	(3.195)	(3.014)
carrier-time fixed effects	yes	yes
handset fixed effects	yes	yes
service fee elasticity		
average	-3.312	-2.967
median	-3.389	-3.033
standard deviation	0.934	0.838
handset price elasticity		
average	-0.588	-0.524
median	-0.461	-0.410
standard deviation	0.455	0.404
Sargan stat/Hansen's J-stat	0.715	0.841
(p-value)	(0.398)	(0.359)

Notes: The instrumental variables are the average age and average consumer satisfaction for similar products offered by rival carriers.

Results from the dynamic model suggest an average own service-fee elasticity of -2.97, while the static-version estimate is -3.31. Elasticity estimates for handset price are in the inelastic range and constitute -0.52 and -0.59 for the dynamic and static models, respectively. Such low elasticity measures are consistent with handsets being subsidized. Figure 6 reports histograms for service fee and handset own price elasticities from the dynamic model. Typical estimates of the own price elasticity in the existing literature are slightly lower; for example, Ingraham and Sidak (2004) and Caves (2011) report -1.29 and -2.1, respectively.

Estimates from our structural model can be used to obtain predictions for churn rates (the probability that a consumer switches away) as well as carrier revenues from ETF payments. Summary statistics are reported in Table 4. On average, churn rates are estimated to be about 2 percent per month, which is consistent with the figures reported by, e.g., Weiergräber (2019). The highest churn rates are estimated for AT&T and Verizon followed by Sprint, T-Mobile and other independent operators. Our estimates suggest that wireless operators earn about 1.94 dollars per month per subscriber from ETF payments. As in the case of

Figure 6: Distribution of own price elasticity for all products



churn rates, Verizon and AT&T earn the most while operators classified as 'Other' earn the least. We will use estimates of revenues generated by ETF payments in Section 7 when we present results from our full equilibrium counterfactual simulations.

Table 4: Monthly churn rates and revenues from ETFs by carrier, structural model

carrier	churn rates			ETF-revenues/subscriber		
	mean	median	st.dev.	mean	median	st.dev.
ATT	0.03	0.03	0.00	2.53	2.52	0.16
OTH	0.01	0.01	0.00	0.84	0.85	0.12
SPR	0.02	0.02	0.00	1.91	1.93	0.50
TMO	0.01	0.01	0.00	1.27	1.35	0.15
VER	0.03	0.04	0.01	3.14	3.13	0.08
average	0.02	0.02	0.01	1.94	1.93	0.87

Notes: Revenues from ETFs are provided at the monthly level assuming a market size of one.

Initial conditions and terminal-period beliefs. Our main specification assumes all consumers hold the outside option at the beginning of period $t = 1$, while consumers believe handset prices, service fees, and mean flow utilities evolve according to an AR(1) process without innovation after the final sample period. In Appendix B.3, we investigate the robustness of our results to alternative assumptions on initial and terminal conditions by re-estimating the model under various alternative scenarios. To evaluate the implications of our initial-conditions assumption, we assume that the wireless market emerged 15 periods before our sample; pre-sample prices and quality levels are assumed to be random perturbations of their values at $t = 1$, or to follow an AR(1) process with or without innovation. To evaluate our terminal-period assumption, we assume that post-sample prices and qualities stay constant, or are given by random perturbations of their values at $t = T$, or follow an AR(1) process with or without innovation. Various combinations of those assumptions have been tested; see Appendix B.3 for a complete description of each robustness check. Overall, we find that coefficient estimates vary little across our experiments (see Tables 18 and 19). For example, the highest and lowest price-coefficient estimates are -8.053 (2.887) and -8.594 (2.056), respectively. From this, we conclude that the error we may incur due to our assumptions on initial and terminal conditions is unlikely to affect our main findings.

Alternative sets of instrumental variables. We have conducted extensive robustness checks for various sets of instrumental variables. Alternative estimation results and counterfactuals can be found in Appendix B.4. As we discuss there, alternative choices of instruments cannot be discriminated according to the overidentifying restrictions tests because none of the specifications is rejected. Furthermore, the t-test does not reject similarity in the parameter estimates across specifications. We selected our main specification (which uses as instruments the average age and average consumer satisfaction for similar products offered by rival carriers) on the ground that it minimizes the share of products for which the supply-side model of Section 7.2 gives rise to negative marginal cost predictions. We use this selection criterion because the estimation of the demand model does not rely on supply-side moment conditions, which, if included, would not admit negative cost estimates.

Consumer heterogeneity. Next, we turn to heterogeneous-consumer versions of the structural model. As discussed in Section 4, to facilitate the identification of type-specific price coefficients we augment our GMM criterion function by micro-moments (see equation (12)). Those additional moments significantly improve the precision of our estimates.

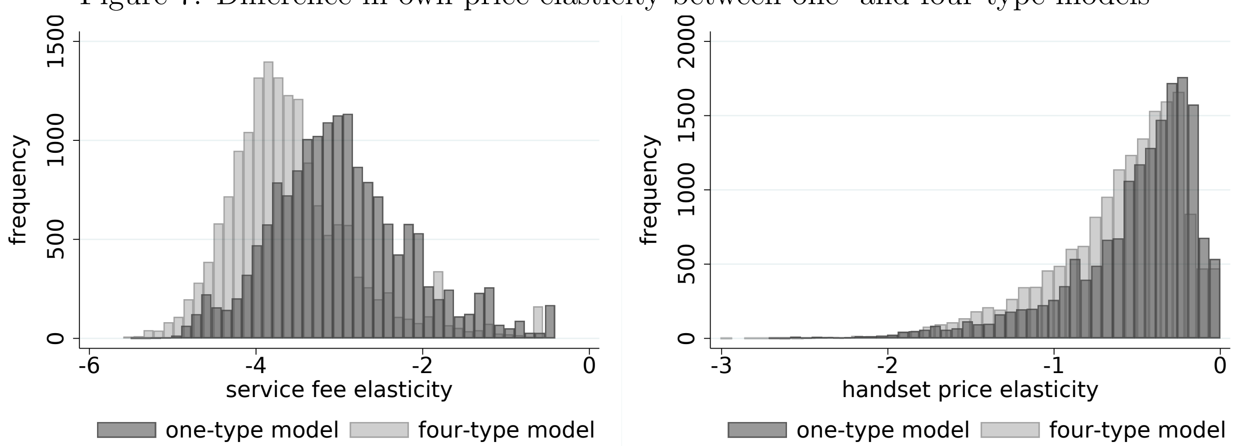
Table 5 summarizes estimation results for various definitions of consumer types based on age, income, or age-income groups. Price coefficient estimates for the two-type model with high- and low-income consumers are reported in column (1). Results from the two-type model with young and old consumers can be found in column (2). Column (3) summarizes estimates from our richest four-type model with consumers tabulated into high and low types according to both their age and income.

Parameter estimates from the four-type model suggest a slightly higher own elasticity with respect to service fee and handset price than in the case without consumer heterogeneity. Figure 7 overlays elasticity histograms for the one- and four-type models. Differences in elasticities with respect to service fees appear slightly larger.

Table 5: Estimation results for heterogeneous consumers

type	(1) income	(2) age	(3) age < 45	(3) age ≥ 45
income, $< 50K$	-8.777		-10.483	-12.953
(s.e.)	(2.103)		(2.246)	(2.239)
income, $\geq 50K$	-7.805		-5.283	-11.152
(s.e.)	(2.102)		(2.043)	(2.248)
age, < 45		-7.068		
(s.e.)		(2.151)		
age, ≥ 45		-9.759		
(s.e.)		(2.165)		
carrier-time dummy	yes	yes	yes	
handset dummy	yes	yes	yes	
Hansen J-stat	1.419	1.357	2.526	
(p-value)	(0.492)	(0.507)	(0.283)	

Figure 7: Difference in own price elasticity between one- and four-type models



7 Counterfactual simulations

We begin by describing partial equilibrium counterfactual simulations (Section 7.1). We refer to those as partial because they rely on demand-side estimates only: In those experiments, we do not allow service providers to re-optimize service fees. Instead, we calculate the compensating proportional change in service fees that would offset the consumer welfare gains from eliminating ETFs. The supply-side structural model is introduced and estimated in Section 7.2. We use it to conduct full-equilibrium counterfactual experiments in Section 7.3.

7.1 Partial equilibrium counterfactuals

Our partial equilibrium analysis considers four counterfactual scenarios. First, we set all ETFs to zero and solve the consumer's dynamic problem holding handset prices and service fees fixed (line "No, purchased at obs. prices"). Second, we assume that when ETFs are eliminated, handset prices are no longer subsidized (line "No, purchased at new prices").[20] Third, for each handset, we calculate a hypothetical per-period rental price, obtained by estimating the handset depreciation rate using prices reported in the survey. This allows us to remove both sources of dynamics by setting ETFs to zero and allowing consumers to rent handsets on a per-period basis (line "No, rented"). Here, we assume that a handset can be rented every period at a price equal to the value of its depreciation. Finally, we allow consumers to rent handsets while firms still use ETFs (line "Yes, rented"). Summary statistics for the changes in consumer welfare and market shares are reported in Table 6.

Table 6: Summary statistics for changes in consumer welfare (value function for each holding) and market shares relative to the observed outcomes, one-type model

counterfactual scenario		mean	p50	min	max	sd
ETFs	handset	change in value functions				
No	purchased at obs. prices	0.76	0.73	0.67	0.98	0.05
No	purchased at new prices	0.48	0.47	0.38	0.68	0.04
No	rented	1.16	1.13	1.02	1.43	0.06
Yes	rented	0.19	0.19	0.16	0.21	0.01
ETFs	handset	change in market shares				
No	purchased at obs. prices	0.48	0.45	-0.76	2.25	0.35
No	purchased at new prices	0.63	0.63	-0.89	3.97	0.59
No	rented	0.70	0.41	-0.87	18.50	1.08
Yes	rented	0.31	0.12	-0.60	8.01	0.68

Notes: Service fees are held fixed; changes are percentage changes relative to the factual outcome.

As expected, the highest increase in consumer welfare (116 percent) is achieved by removing ETFs and simultaneously allowing consumers to lease handsets. Interestingly, the rental option alone, which eliminates the dynamics generated by handset durability, improves consumer welfare by 19 percent. The elimination of ETFs under current handset prices raises consumer welfare by 76 percent on average. In the more realistic scenario in which handset prices are no longer subsidized after ETFs have been eliminated, the welfare improvement, 48 percent, is less impressive. Naturally, the increase in consumer utility from the available products increases market shares, with the change in product-specific market shares ranging between 31 and 70 percent on average.

Counterfactual results for the four-type model can be found in Table 24 in Appendix B.5. That version of the model, due to its higher estimated aggregate price sensitivity, suggests larger gains in each of the scenarios. For example, the elimination of ETFs at observed handset

[20] To obtain unsubsidized handset prices, we used the maximum price observed in our survey data for a given handset model across all possible types of subscription (i.e., contract and prepaid).

prices improves consumer welfare by 90 percent instead of 76 percent without heterogeneity. Similarly, at new handset prices, the multi-type model predicts a 58-percent improvement (compared to 48 percent without heterogeneity).[21]

ETFs versus service fees. Before specifying the supply side and making stronger assumptions, we provide a brief analysis of the compensating change in service fee that would offset the welfare gains from the elimination of ETFs. That is, assuming that all service fees increase by x percent after ETFs have been eliminated, we solve for the x^* such that the average difference between the factual and counterfactual value functions is zero. Table 7 reports the results for the one- and four-type versions of the dynamic model. At new (resp. observed) handset prices, service fees would have to increase by around 30 percent (resp. 40 percent) to offset the consumer welfare gains from ETF elimination. The compensating increase in service fees is slightly lower in the four-type model, which is intuitive since that model features higher estimated price-sensitivity coefficients.[22]

Table 7: Change in service fees offsetting consumer gains from ETF elimination, %

type of compensating change	one-type model	four-type model
increase in service fees at obs. h-set prices	42.59	41.21
increase in service fees at new h-set prices	31.70	29.60

Notes: Offsetting price increase is computed such that the difference between consumer value functions before the ETF elimination and consumer value functions after the ETF elimination with corresponding proportional change in service fees is zero on average.

7.2 Supply of wireless services

Framework. To recover the wireless service providers' cost structure and carry out counterfactuals in which service fees endogenously adjust, we introduce and estimate a supply-side model with forward-looking firms that are able to predict future sequences of payoff-relevant variables and account for dynamic consumer behavior. For the sake of tractability and computational feasibility, we will however need to impose a number of restrictions on, *inter alia*, firms' behavior and rationality, which we describe in detail below. A first simplification is that we focus on the one-type demand model from now on.

We begin by introducing new notation. Let $\mathcal{J}_t^c$ be the set of products offered by carrier c in period t. The vector of service fees (for all periods and products in our sample) is denoted

[21] To illustrate the relationship between demand elasticity and consumer welfare predictions, we repeat this exercise for alternative versions of the model without consumer heterogeneity—see Table 20 in Appendix B.4. The welfare comparisons are reported in Tables 21 and 22 in the same appendix. The lower estimated price elasticities (see Figures 10 and 11) result in more modest welfare improvements. For example, eliminating both ETFs and handset subsidies raises consumer welfare by 27 to 34 percent.

[22] Similarly, for the specifications of the one-type model that deliver lower price-sensitivity coefficients, the offsetting service-fee increase tends to be larger; see Table 20 and 23 in Appendix B.4.

$\boldsymbol{p} = ((p_{jt})_{j \in \mathcal{J}_t})_{1 \le t \le T}$. To remain consistent with our demand-side model, we continue to assume that prices and flow utilities in periods $T+1, \ldots, T'$ are governed by the deterministic AR(1) processes mentioned in Section 4.1.[23] We now make the dependence of consumer shares on service fees explicit by writing $\sigma_{j\tau}[t](\boldsymbol{p})$ (for the share of consumers who have been holding product j since period τ) and $s_{jt}(\boldsymbol{p})$ (for the overall share of consumers who are holding product j in period t). Due to intertemporal demand linkages, those shares depend on the entire vector of (past, present, and future) service fees.

We can now write down firms' intertemporal profits. Consider those consumers who have been holding product $j \in \mathcal{J}_t^c$ since period τ. From each of them, carrier c receives the service fee specified in their contract, $p_{j\tau}$. Subtracting the marginal cost in period t, c_{jt}, and multiplying by $\sigma_{j\tau}[t](\boldsymbol{p})$, we obtain the profits that carrier c earns on those consumers at time t: $(p_{j\tau} - c_{jt})\sigma_{j\tau}[t](\boldsymbol{p})$. Adding up over all possible holdings and time periods, we obtain carrier c's profits (normalized by market size):[24]

$$\pi^c(\boldsymbol{p}) = \sum_{t=1}^{T} \beta^{t-1} \sum_{\tau=1}^{t} \sum_{j \in \mathcal{J}_\tau^c} (p_{j\tau} - c_{jt})\sigma_{j\tau}[t](\boldsymbol{p}). \tag{13}$$

This specification already features two important simplifying assumptions. First, wireless carriers do not internalize the profits derived from ETF payments when choosing service fees.[25] Second, carriers do not internalize profits from selling handsets to consumers.[26]

Next, we introduce two further simplifications. The first one relates to the equilibrium concept. The profit functions in equation (13) are the payoffs of a multistage game of observed actions. The standard equilibrium concept for such games is subgame-perfect equilibrium. Unfortunately, backward induction is computationally infeasible here due to the large number of subgames, the high dimensionality of the firms' action sets, and the complexity of the dynamic consumer choice problem. We thus use an alternative equilibrium concept: equilibrium in open-loop strategies. With open-loop strategies, each firm irrevocably commits *ex ante* to a sequence of prices for all of its products. This approach makes it feasible to recover marginal costs from first-order conditions since we no longer have to worry about

[23] Recall that T' is the number of periods in our extended data set.

[24] To mitigate the effects of extended time periods $T+1, \ldots, T'$ on our cost estimates, we assume that firms put no weight on profits derived in those periods.

[25] One issue we face here is that ETF schedules changed very little during our sample period, which makes it unlikely that wireless carriers were viewing ETFs as short-run strategic instruments. An implication is that, if we allowed carriers to choose ETFs, we would not be confident that the marginal cost of processing those fees could be credibly backed out from first-order conditions. An alternative would be to assume that, although ETFs are not chosen, carriers still internalize the profits they receive from consumers who pay them. The drawback here is again that we would have no reliable way of estimating the cost of processing those fees.

[26] The reason for this simplification is that the wholesale and retail prices of handsets are likely to be the outcome of complex negotiations between wireless carriers and handset manufacturers. Modeling such negotiations is beyond the scope of this paper, but could be an interesting avenue for future research.

a change in p_{jt} affecting rivals' sequences of prices in the continuation subgame.

Finally, we assume that firms behave as if they believed that consumers holding product j in period t pay the going price for that product (p_{jt}) instead of the contract price ($p_{j\tau}$, if the consumer has been holding that product since period τ).[27] Under this assumption, firm c's perceived profit function becomes

$$\pi^c(\boldsymbol{p}) = \sum_{t=1}^{T} \beta^{t-1} \sum_{j \in \mathcal{J}_t^c} (p_{jt} - c_{jt}) s_{jt}(\boldsymbol{p}). \tag{14}$$

This assumption is also made for tractability reasons, as it allows us to sidestep the arduous task of numerically evaluating the partial derivative of $\sigma_{j\tau}[t]$ with respect to p_{kt} for every pair of time periods, (τ, t), and every pair of products sold by carrier c, $(j,k) \in (\mathcal{J}_\tau^c)^2$.

Under the above simplifying assumptions, our supply-side model is a one-shot, simultaneous-moves game in which each carrier c chooses a sequence of prices for all of its products so as to maximize the profit function in equation (14). (Carriers classified as "Other" are assumed to maximize their joint profits; this is relaxed in Section 7.3.) To the best of our knowledge, no known equilibrium existence result (e.g., Caplin and Nalebuff, 1991; Nocke and Schutz, 2018) applies to our model due to intertemporal demand linkages. We thus assume that a Nash equilibrium exists, and that it is characterized by standard first-order conditions.

Recovering marginal costs. The first-order condition for product $j \in \mathcal{J}_t^c$ in period t is

$$\beta^{t-1} s_{jt}(\boldsymbol{p}) + \sum_{\tau=1}^{T} \beta^{\tau-1} \sum_{k \in \mathcal{J}_\tau^c} \frac{\partial s_{k\tau}(\boldsymbol{p})}{\partial p_{jt}} (p_{k\tau} - c_{k\tau}) = 0. \tag{15}$$

Let $\boldsymbol{D^c}(\beta)$ and $\boldsymbol{S^c}(\beta)$ denote the properly discounted matrix of market share derivatives and vector of market shares for all products offered by carrier c, respectively. (We set β equal to 0.95, as we did for consumers.) The vectors of service fees and marginal costs of carrier c are denoted $\boldsymbol{p^c}$ and $\boldsymbol{c^c}$. The system of equations (15) (for every t and $j \in \mathcal{J}_t^c$) can then be rewritten as $\boldsymbol{S^c}(\beta) + \boldsymbol{D^c}(\beta)(\boldsymbol{p^c} - \boldsymbol{c^c}) = \boldsymbol{0}$, which can be readily inverted as

$$\boldsymbol{c^c} = \boldsymbol{p^c} + \boldsymbol{D^c}(\beta)^{-1} \boldsymbol{S^c}(\beta)$$

to recover marginal costs.

Table 8 reports statistics on the proportion of positive marginal cost predictions for our main specification of the demand model, as well as two alternative specifications. Estimation results for those alternative specifications are reported in Table 20 in Appendix B.4, where

[27] On the demand side, consumers do perceive the prices they pay as being fixed in the contract.

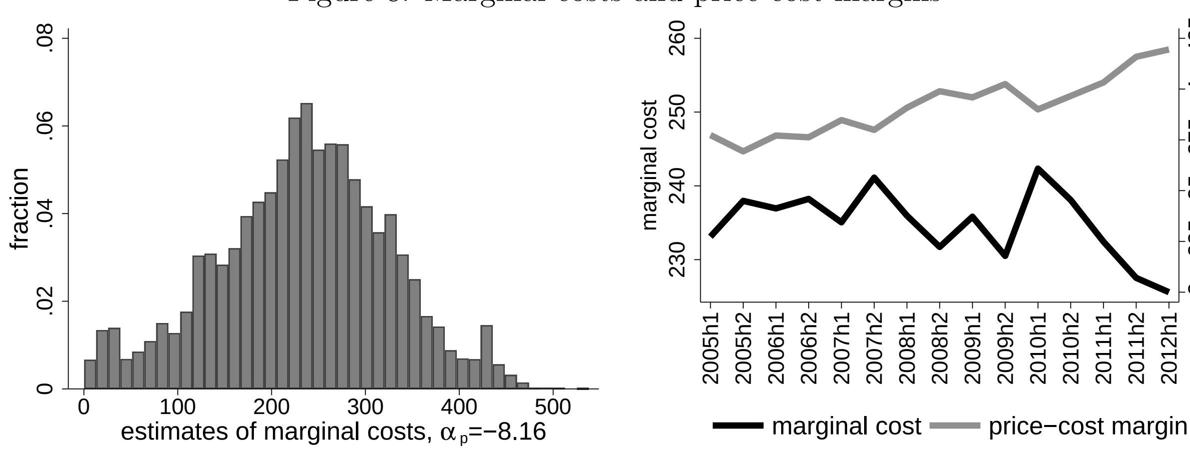
our main model is listed as specification (3). As mentioned in Section 6, we elected to use specification (3) as our main specification because it is the one that gives rise to the lowest proportion of negative marginal cost estimates.

Table 8: Shares of positive marginal cost estimates by specification by carrier

carrier	N	share of positive marginal costs, $mc_{jt} > 0$		
		main (spec. (3)), $\alpha_p = -8.16$	spec. (2), $\alpha_p = -6.47$	spec. (1), $\alpha_p = -5.43$
ATT	4,046	0.99	0.97	0.96
OTH	3,534	0.93	0.86	0.82
SPR	2,668	0.97	0.94	0.92
TMO	2,524	0.99	0.97	0.96
VER	3,873	0.99	0.98	0.96

The distribution of estimated marginal costs and the evolution of average marginal costs and price cost margins over time are presented in Figure 8. Figure 9 reports the evolution of marginal costs and price-cost margins broken down by carrier. Marginal costs estimated for the group of carriers labeled as "Other" appear to be the lowest (and their price-cost margins consequently the highest). The intuition may be that most of the smaller carriers originated as subsidiaries of the big four. As they often rely on the infrastructure (cell towers) built by their larger rivals, it is conceivable that their lower marginal costs reflect not only their lower quality of service but also lower infrastructure maintenance costs.

Figure 8: Marginal costs and price-cost margins

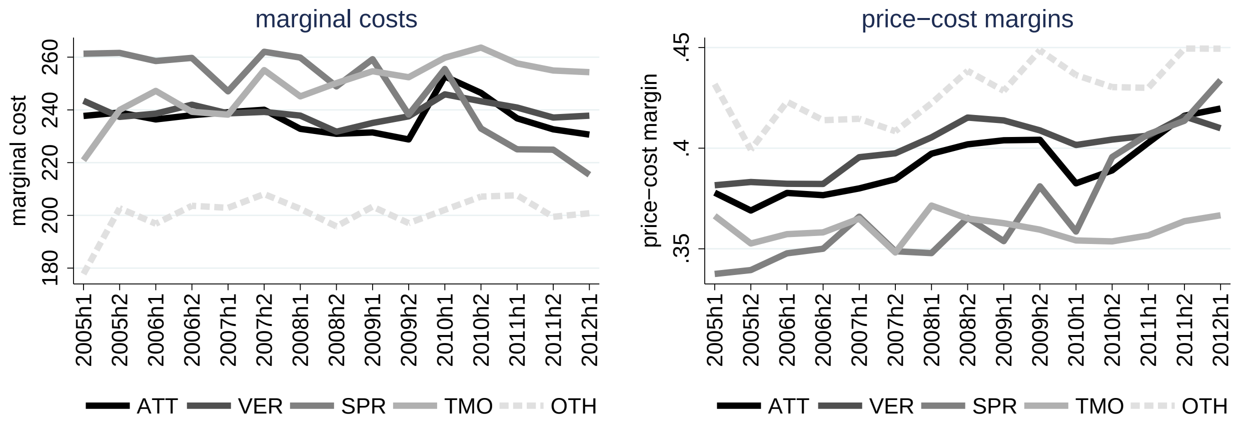


Notes: Averaged across products, negative values of marginal costs excluded.

7.3 Full-equilibrium counterfactual simulations

We now assume that carriers play the game described in the previous subsection, but without ETFs. To maintain consistency with the way in which marginal costs were recovered, we

Figure 9: Marginal costs and price-cost margins by carrier by time



Notes: Averaged across products, negative values of marginal costs excluded.

continue to assume that firms maximize the profit functions defined in equation (14)—that is, consumers pay the service fees specified in their contract but firms behave as if they paid going prices. For handset prices, we use observed (i.e., subsidized) prices. To find the equilibrium of the no-ETF game, we discretize half-yearly service fees so that price changes relative to the factual are in increments of one dollar.[28] The algorithm circles through each product and searches for the service fee that maximizes the profits of the wireless carrier offering this product. Termination occurs if no more improvement can be found in a given loop over all products.[29]

The results are reported in Table 9. The elimination of ETFs induces wireless service providers to increase their service fees by 2 to 5 percent. The largest increase is predicted for Verizon (5.17 percent), followed by AT&T (4.2 percent) and Sprint (3.93 percent). T-Mobile and smaller carriers increase prices the least. There is no clear pattern in price changes over time. The right panel of Table 9 reports percentage changes in profits from service fees—profits from ETF payments are not included; see the discussion below. Our model predicts that the largest beneficiaries from ETF elimination are the smaller carriers, T-Mobile and Sprint. The profits of AT&T and Verizon increase by 46 to 50 percent, while other carriers gain between 84 and 89 percent.

Table 10 reports consumer welfare under three alternative scenarios. The first column reports, for each wireless operator, factual consumer surplus in dollars, as measured by the dynamic value function. The next two columns, labeled “no ETF, old service fees”, report

[28] Given the high dimensionality of carriers’ choice sets, discretization is necessary to make our simulations computationally feasible. Note that our price grid is quite fine, as one dollar corresponds to one percent of the standard deviation of half-yearly service fees in our sample, and to 0.27 percent of the average service fee.

[29] If profit functions are concave and the algorithm terminates, then the price vector that obtains is an open-loop equilibrium (assuming the grid is not too coarse). Since checking payoff concavity is impractical, we experimented with multiple starting values; we always obtained convergence to the same price vector.

Table 9: Change in service fees and carrier profits without ETF, optimal prices

time	% change in service fees					% change in profits				
	ATT	OTH	SPR	TMO	VER	ATT	OTH	SPR	TMO	VER
2005-h1	4.53	1.87	5.22	3.77	4.29	83.16	133.14	126.26	133.04	73.12
2005-h2	4.40	1.77	4.82	3.02	5.06	71.32	114.38	107.00	116.60	61.55
2006-h1	4.65	1.95	4.90	3.11	5.07	67.32	111.90	103.05	110.55	58.24
2006-h2	4.25	2.03	4.84	3.07	4.91	59.39	102.73	94.64	99.71	50.98
2007-h1	4.02	2.05	4.60	2.94	4.58	51.23	91.47	85.15	88.74	42.88
2007-h2	3.79	1.87	3.92	2.61	4.48	45.37	82.79	78.22	80.72	37.12
2008-h1	3.77	1.84	3.57	2.75	4.18	40.30	75.16	71.90	73.70	32.66
2008-h2	3.61	1.95	3.47	2.68	4.12	37.73	71.45	68.63	70.42	30.33
2009-h1	3.50	2.03	2.87	2.62	3.96	35.79	69.75	67.33	68.85	28.57
2009-h2	3.50	2.34	3.05	2.52	5.04	34.41	68.44	66.06	67.42	36.58
2010-h1	3.50	2.05	2.42	2.19	5.84	39.61	61.61	59.38	60.51	49.47
2010-h2	5.02	1.71	2.50	1.95	6.39	55.67	53.76	51.56	52.75	53.19
2011-h1	5.75	1.85	2.64	2.06	7.51	61.59	54.15	50.53	53.04	61.54
2011-h2	3.98	2.88	4.79	3.74	5.31	33.06	78.83	113.57	128.00	38.29
2012-h1	4.83	3.28	5.41	3.39	6.81	32.51	81.19	116.14	128.35	37.42
average	4.20	2.10	3.93	2.83	5.17	49.90	83.38	83.96	88.83	46.13

consumer surplus and its percentage increase relative to the factual situation for the scenario in which ETFs are abolished but service fees do not to adjust. The last two columns report those figures for the scenario in which ETFs are abolished and service fees do adjust. Our estimates suggest that the average consumer valuation of the wireless market is around 2,350 dollars in the factual; this figure varies very little across carriers. The elimination of ETFs increases consumer value functions by 76 percent, so that the new lifetime value of the wireless market increases to 4,130 dollars. When service providers finally adjust their prices, consumer welfare declines but remains 67 percent higher than in the factual situation.

Table 10: Changes in consumer value functions after ETF elimination

carrier	factual	no ETF, old service fees		no ETF, new service fees	
	\$ value	\$ value	% diff.	\$ value	% diff.
ATT	2,349.46	4,132.79	75.90	3,934.64	67.47
OTH	2,328.91	4,110.00	76.48	3,913.67	68.05
SPR	2,357.66	4,141.61	75.67	3,942.81	67.23
TMO	2,342.14	4,125.16	76.13	3,927.57	67.69
VER	2,357.71	4,141.41	75.65	3,942.59	67.22
average	2,347.18	4,130.20	75.97	3,932.26	67.53

Table 11 reports additional information on carriers' average monthly profits. Recall that profits derived from service fees increase by 50 to 90 percent after ETFs have been eliminated. However, if we add expected ETF payments to the carrier profits, the situation is different: If the cost of processing ETF payments were zero, the elimination of long-term contracts would reduce profits by 17 to 25 percent. This can be seen in line "% of factual with ETF payments" of Table 11, which reports profits in the new equilibrium without ETFs as a percentage of the factual profits from both service fees and ETF payments.

Table 11: Wireless carriers' monthly profits under alternative scenarios

profit sources and comparison	ATT	OTH	SPR	TMO	VER
Factual					
Profits from service fees	2.55	0.68	1.54	1	3.37
Revenues from ETF payments	2.53	0.84	1.91	1.27	3.14
Total, factual	5.08	1.52	3.45	2.27	6.51
No ETF, old service fees					
Profits from service fees	3.49	1.09	2.59	1.68	4.53
Revenues from ETF payments	0.00	0.00	0.00	0.00	0.00
Total, No ETF, old service fees	3.49	1.09	2.59	1.68	4.53
% of factual without ETF payments	136.86	160.29	168.18	168.00	134.42
% of factual with ETF payments	68.70	71.71	75.07	74.01	69.59
No ETF, new service fees					
Profits from service fees	3.83	1.22	2.85	1.86	4.91
Revenues from ETF payments	0.00	0.00	0.00	0.00	0.00
Total	3.83	1.22	2.85	1.86	4.91
% of factual without ETF payments	150.20	179.41	185.06	186.00	145.70
% of factual with ETF payments	75.39	80.26	82.61	81.94	75.42
Cost of ETF to rationalize "No ETF" policy	1.25	0.30	0.60	0.41	1.60
% of No ETF, old service fees	109.74	111.93	110.04	110.71	108.39

Notes: Monthly profits are computed for a market of size one and expressed in USD.

Since it seems unlikely that the marginal cost of processing ETF payments is zero, we calculate the minimum unit processing cost such that wireless service providers are better off without ETFs. These costs are reported in line "Cost of ETF to rationalize "No ETF" policy." For profits to be higher without ETFs, the monthly per-consumer cost of processing such payments would have to exceed 1.60 dollars for Verizon, 1.25 dollars for AT&T, 60 cents for Sprint, and less than 50 cents for smaller carriers and T-Mobile.

Robustness analysis. To recover marginal costs and simulate the full-equilibrium counterfactual, we made two important assumptions: First, firms believe that consumers pay going prices instead of contract prices; second, the carriers classified as "Other" (e.g., Boost Mobile, Cricket, MetroPCS, Virgin Mobile, etc.) maximize that group's joint profits. We evaluate the quantitative implications of those assumptions in turn.

To assess the role of the going-price assumption, we simulate another full-equilibrium counterfactual where producers hold the correct belief that consumers pay the service fees specified in their contract. Table 12 reports summary statistics for the difference in new equilibrium prices. Equilibrium prices under the contract-price and going-price assumptions are very similar. Specifically, only about 15 percent of product prices are different across the two scenarios, and the difference is at most six dollars. Our takeaway is that the error we incur when recovering marginal costs and simulating the no-ETF counterfactual under the going-price assumption is minor and thus unlikely to affect our main findings.

Table 12: Equilibrium service fees under the contract-price and going-price assumptions

assumption	mean	median	min	max	sd
Contract-price assumption	375.94	385.45	0.00	697.06	105.25
Going-price assumption	375.96	385.36	0.00	697.06	105.26
Difference (levels)	-0.02	0.00	-4.00	6.00	0.44

To evaluate the role of the joint profit maximization assumption for the group "Other", we simulate another full-equilibrium counterfactual where all products in that group maximize individual profits. Table 13 reports the difference in equilibrium prices. Relative to the factual, in the no-ETF counterfactual, the prices of products in the group "Other" increase by 2.32 percent on average under the joint profit maximization assumption. Unsurprisingly, under individual profit maximization, those prices decline by 1.58 percent. On the other hand, the prices set by the major carriers are barely affected by what the group "Other" maximizes. Averaging across all carriers, counterfactual prices differ by only 0.82 percent across the two scenarios. From this, we conclude that our assumption about what the group "Other" maximizes does not significantly affect our main findings.

Table 13: Service fees under individual vs joint maximization for OTH

carrier	average service fees			% change in service fees		
	(1) factual	(2) joint	(3) individual	(1) vs (2)	(1) vs (3)	(2) vs (3)
ATT	375.88	390.70	390.37	4.25	4.16	-0.09
OTH	311.85	318.54	307.19	2.32	-1.58	-3.78
SPR	363.89	376.90	376.70	3.76	3.70	-0.06
TMO	380.41	390.18	390.02	2.75	2.70	-0.05
VER	384.86	404.39	403.99	5.44	5.33	-0.10
average	363.38	376.14	373.66	3.70	2.86	-0.82

8 Conclusions

We have studied the welfare effects of early termination fees in the US wireless industry. To gain intuition, we developed and solved a stylized theoretical model in which firms choose whether to impose switching costs on consumers in the form of ETFs and then compete in service fees. An important takeaway is that ETFs make consumers perceive the various products as being less differentiated, and thus intensify competition. This effect can be so strong that consumers are better off in an equilibrium with ETFs (despite their inability to switch suppliers), whereas firms can be worse off (despite their ability to lock in consumers). Moreover, firms may well face a coordination problem, as, for plausible parameter values, equilibria in which all firms use ETFs coexist with equilibria in which no firm uses ETFs.

Building on these insights, we developed and estimated a dynamic structural model of the US wireless industry. That structural model accounts for multiple competing service providers, finite level of ETFs, the multi-product nature of the wireless service providers, correlation in per-period flow utilities across carriers, and other important details that were omitted in our theoretical model. Estimation results suggest a significant increase in consumer surplus as a result of the elimination of ETFs. To offset these gains, service fees would have to rise by 30 to 40 percent.

Full equilibrium counterfactuals predict an increase in service fees by 2.10 to 5.17 percent. Despite this, consumers are better off in the new equilibrium, with an average increase in welfare of about 68 percent. There is also a substantial increase in profits gathered by means of service fees, ranging from 50 to 80 percent depending on the carrier. However, the overall effect on producer surplus becomes less clear once profits from ETF payments are accounted for. In particular, if the monthly per-consumer cost of processing ETF payments is sufficiently high (with the cutoff ranging from 40 cents to 1.60 dollars depending on the carrier), then producers are also better off without ETFs. In this case, we would conclude that the elimination of ETFs is welfare enhancing overall.

References

Aguirregabiria, V., and P. Mira (2002): "Swapping the nested fixed point algorithm: a class of estimators for discrete Markov decision models," *Econometrica*, 70(4), 1519–1543.

——— (2007): "Sequential estimation of dynamic discrete games," *Econometrica*, 75(1), 1–53.

Aguirregabiria, V., and A. Nevo (2013): "Recent Developments in Empirical IO: Dynamic Demand and Dynamic Games," in *Advances in Economics and Econometrics*, ed. by D. Acemoglu, M. Arellano, and E. Dekel, vol. 3, Econometric Society Monographs 2, pp. 53–122. Cambridge University Press.

Arcidiacono, P., and R. Miller (2011): "Conditional choice probability estimation of dynamic discrete choice models with unobserved heterogeneity," *Econometrica*, 79(6), 1823–1867.

Bajari, P., L. Benkard, and J. Levin (2007): “Estimating dynamic models of imperfect competition,” *Econometrica*, 75(5), 1331–1370.

Bedre-Defolie, O., and G. Biglaiser (2017): “Contracts as a Barrier to Entry in Markets with Nonpivotal Buyers,” *American Economic Review*, 107(7), 2041–2071.

Beggs, A., and P. Klemperer (1992): “Multi-Period Competition With Switching Costs,” *Econometrica*, 60, 651–666.

Berry, S. (1994): “Estimating Discrete-Choice Models of Product Differentiation,” *RAND Journal of Economics*, 25, 242–262.

Berry, S., J. Levinsohn, and A. Pakes (1995): “Automobile Prices in Market Equilibrium,” *Econometrica*, 63, 841–890.

——— (2004): “Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market,” *Journal of Political Economy*, 112(1), 68–105.

Blumberg, S. J., and J. V. Luke (2015): “Wireless Substitution: Early Release of Estimates From the National Health Interview Survey, July-December 2014,” Discussion paper, U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, Division of Health Interview Statistics, National Center for Health Statistics.

Caplin, A., and B. Nalebuff (1991): “Aggregation and Imperfect Competition: On the Existence of Equilibrium,” *Econometrica*, 59(1), 25–59.

Caves, K. W. (2011): “Quantifying Price-Driven Wireless Substitution in Telephony,” *Telecommunications Policy*, 35(11), 984–998.

CTIA (2015): “CTIA’s Wireless Industry Summary Report, Year-End 2014 Results,” Discussion paper, CTIA-The Wireless Association.

Cullen, J., and O. Shcherbakov (2010): “Measuring Consumer Switching costs in the Wireless Industry,” Unpublished manuscript. Yale University and Harvard University.

Doganoglu, T. (2010): “Switching Costs, Experience Goods and Dynamic Price Competition,” *Quantitative Marketing and Economics (QME)*, 8(2), 167–205.

Dube, J.-P., G. Hitsch, and P. Rossi (2009): “Do Switching Costs Make Markets Less Competitive?,” *Journal of Marketing Research*, 46(4), 435–445.

Fabra, N., and A. Garcia (2015): “Market Structure and the Competitive Effects of Switching Costs,” *Economics Letters*, 126(C), 150–155.

Fudenberg, D., and J. Tirole (1991): *Game Theory*. The MIT Press, Cambridge, Massachusetts.

Gowrisankaran, G., and M. Rysman (2012): "Dynamics of Consumer Demand for New Durable Goods," *Journal of Political Economy*, 120(6), 1173–1219.

Hendel, I., and A. Nevo (2006): "Measuring the implications of sales and consumer inventory behavior," *Econometrica*, 74, 1637–1673.

Hotz, J., and R. Miller (1993): "Conditional choice probabilities and the estimation of dynamic models," *The Review of Economic Studies*, 60(3), 497–529.

Hotz, J., R. Miller, S. Sanders, and J. Smith (1994): "A simulation estimator for dynamic models of discrete choice," *The Review of Economic Studies*, 61(2), 265–289.

Ingraham, A., and G. Sidak (2004): "Do States Tax Wireless Services Inefficiently? Evidence on the Price Elasticity of Demand.," *Virginia Tax Review*, 24(2), 249–261.

Klemperer, P. (1987): "Markets with Consumer Switching Costs," *The Quarterly Journal of Economics*, 102, 375–394.

——— (1995): "Competition when Consumers Have Switching Costs: An Overview with Applications to Industrial Organization, Macroeconomics, and International trade," *The Review of Economic Studies*, 62, 515–539.

Magnac, T., and D. Thesmar (2002): "Identifying discrete decision processes," *Econometrica*, 70(2), 801–816.

Manski, C. F. (1993): "Dynamic choice in social settings. Learning from the experiences of others.," *Journal of Econometrics*, 58, 121–136.

Melnikov, O. (2013): "Demand for differentiated durable products: the case of the U.S. computer printer market," *Economic Inquiry*, 51(2), 1277–1298.

Nocke, V., and N. Schutz (2018): "Multiproduct-Firm Oligopoly: An Aggregative Games Approach," *Econometrica*, 86(2), 523–557.

Nosal, K. (2012): "Estimating Switching Costs for Medicare Advantage Plans," Unpublished manuscript. University of Arizona.

Pakes, A., M. Ostrovsky, and S. Berry (2007): "Simple estimators for the parameters of discrete dynamic games (with entry/exit examples)," *RAND Journal of Economics*, 38(2), 373–399.

PESENDORFER, M., AND P. SCHMIDT-DENGLER (2008): "Asymptotic least squares estimators for dynamic games," *The Review of Economic Studies*, 75, 901–928.

PETRIN, A. (2002): "Quantifying the Benefits of New Products: The Case of the Minivan," *The Journal of Political Economy*, 110(4), 705–729.

PEW RESEARCH CENTER (2015): "The Smartphone Difference," Discussion paper, Pew Research Center.

RHODES, A. (2014): "Re-Examining the Effects of Switching Costs," *Economic Theory*, 57(1), 161–194.

RUST, J. (1987): "Optimal replacement of GMC bus engines: an empirical model of Harold Zurcher," *Econometrica*, 55(5), 999–1033.

——— (1994): "Structural estimation of Markov decision processes," in *Handbook of Econometrics*, ed. by R. Engle, and D. McFadden, vol. 4, chap. 51, pp. 3081–3143. Elsevier Science B.V.

SCHIRALDI, P. (2011): "Automobile Replacement: A Dynamic Structural Approach," *RAND Journal of Economics*, 42(2), 266–291, Summer.

SHCHERBAKOV, O. (2016): "Measuring consumer switching costs in the television industry," *The RAND Journal of Economics*, 47(2), 366–393.

SOMAINI, P., AND L. EINAV (2013): "A Model of Market Power in Customer Markets," *Journal of Industrial Economics*, 61(4), 938–986.

VON WEIZSÄCKER, C. C. (1984): "The Costs of Substitution," *Econometrica*, 52(5), 1085–1116.

WEIERGRÄBER, S. (2019): "Network Effects and Switching Costs in the US Wireless Industry," Unpublished manuscript. Indiana University.

Appendix

A Proofs

This section is organized as follows. We begin by studying the so-called mixed subgame, in which one firm uses ETFs while the other one does not (Appendix A.1). Next, we derive equilibrium behavior at time $t = -1$, i.e., when firms decide whether to use ETFs, and thus prove Proposition 1 (Appendix A.2).

A.1 The mixed subgame

To fix ideas, suppose firm 1 uses ETFs and firm 2 does not. Let (p_1^*, p_2^*) be a candidate stationary subgame-perfect equilibrium. We first analyze consumer behavior. Let $U_i(p_1, p_2, x)$ be the value of a consumer with type x when she buys from firm i, current-period prices are (p_1, p_2), and future prices are expected to be (p_1^*, p_2^*). Then,

$$U_1(p_1, p_2, x) = \delta - x - p_1 + \frac{\beta_c}{1-\beta_c}\left(\delta - \frac{1}{2} - p_1\right),$$
$$U_2(p_1, p_2, x) = \delta - (1-x) - p_2 + \beta_c \mathbb{E}_y \max\left(U_1(p_1^*, p_2^*, y), U_2(p_1^*, p_2^*, y)\right).$$

To understand the first value function, note that if the consumer buys from firm 1 at price p_1 in the current period, then she will have to purchase from the same firm at the same price in all subsequent periods. (The term 1/2 reflects expected future transport costs.) On the other hand, if the consumer buys from firm 2, then she will get to choose which firm to buy from in the next period, as seen in the second value function. Define

$$u_1^* = \frac{1}{1-\beta_c}\left(\delta - \frac{1}{2}\beta_c\right), \tag{16}$$
$$\text{and } u_2^* = \delta + \beta_c \mathbb{E}_y \max\left(U_1(p_1^*, p_2^*, y), U_2(p_1^*, p_2^*, y)\right).$$

The location of the marginal consumer, x, satisfies $U_1(p_1, p_2, x) = U_2(p_1, p_2, x)$, yielding

$$x = \frac{1}{2} + \frac{u_1^* - u_2^*}{2} + \frac{p_2 - \frac{p_1}{1-\beta_c}}{2}. \tag{17}$$

In equilibrium, $p_1 = p_1^*$, $p_2 = p_2^*$, the marginal type is given by

$$x^* = \frac{1}{2} + \frac{u_1^* - u_2^*}{2} + \frac{p_2^* - \frac{p_1^*}{1-\beta_c}}{2}, \tag{18}$$

and u_2^* satisfies

$$u_2^* = \delta + \beta_c \left(\int_0^{x^*} \left(u_1^* - \frac{p_1^*}{1-\beta_c} - y \right) dy + \int_{x^*}^1 \left(u_2^* - p_2^* - (1-y) \right) dy \right),$$
$$= \delta + \beta_c \left(\left(u_1^* - \frac{p_1^*}{1-\beta_c} - \frac{1}{2} x^* \right) x^* + \left(u_2^* - p_2^* - \frac{1}{2}(1-x^*) \right) (1-x^*) \right). \quad (19)$$

Next, we turn to firm behavior. Let $V_i(p_1, p_2)$ be the value of firm $i \in \{1, 2\}$ per free buyer when current prices are (p_1, p_2) and future prices are expected to be (p_1^*, p_2^*). Then, using the definition of the marginal type (17),

$$V_1(p_1, p_2) = \frac{1}{1-\beta_f} p_1 \left(\frac{1}{2} + \frac{u_1^* - u_2^*}{2} + \frac{p_2 - \frac{p_1}{1-\beta_c}}{2} \right)$$
$$+ \beta_f \left(\frac{1}{2} + \frac{u_2^* - u_1^*}{2} + \frac{\frac{p_1}{1-\beta_c} - p_2}{2} \right) V_1\left(p_1^*, p_2^*\right). \quad (20)$$

The first term in equation (20) comes from the fact that a consumer whose type is less than the marginal type will buy from firm 1 in the current period, and will be locked in with that firm at the same price in all subsequent periods. The second term reflects the fact that consumers with types above the marginal type do not buy from firm 1 today, and will still be free buyers tomorrow. Firm 2's value function involves similar considerations:

$$V_2(p_1, p_2) = \left(p_2 + \beta_f V_2\left(p_1^*, p_2^*\right)\right) \left(\frac{1}{2} + \frac{u_2^* - u_1^*}{2} + \frac{\frac{p_1}{1-\beta_c} - p_2}{2} \right). \quad (21)$$

Let $v_i^* = V_i\left(p_1^*, p_2^*\right)$, $i = 1, 2$. Those equilibrium values satisfy:

$$v_1^* = \frac{1}{1-\beta_f} p_1^* x^* + \beta_f \left(1 - x^*\right) v_1^*, \quad (22)$$
$$v_2^* = \left(p_2^* + \beta_f v_2^*\right)\left(1 - x^*\right). \quad (23)$$

Taking first-order conditions in equations (20) and (21) and plugging in $p_1 = p_1^*$ and $p_2 = p_2^*$ yields:

$$0 = \frac{1}{1-\beta_f} \left(x^* - \frac{1}{2} \frac{p_1^*}{1-\beta_c} \right) + \frac{1}{2(1-\beta_c)} \beta_f v_1^*, \quad (24)$$
$$0 = 1 - x^* - \frac{1}{2}\left(p_2^* + \beta_f v_2^*\right). \quad (25)$$

To summarize, if (p_1^*, p_2^*) is a stationary subgame-perfect equilibrium, then $(u_1^*, u_2^*, x^*, v_1^*, v_2^*, p_1^*, p_2^*)$ solves equations (16), (18), (19), (22), (23), (24), and (25), and $x^* \in [0, 1]$. We show that this system of equations has a unique solution, and that this solution is indeed a stationary subgame-perfect equilibrium:

Lemma 1. *There exists a unique stationary subgame-perfect equilibrium in the mixed subgame.*

Proof. We drop the star superscripts to ease notation. The proof is analytical, but some of the computations are cumbersome. Details of the calculations can be found in Mathematica file `ETF-Hotelling.nb`.

We approach the problem as follows. Fix some $x \in [0,1]$. Using Mathematica, we show that there exists a unique vector $(u_1(x), u_2(x), v_1(x), v_2(x), p_1(x), p_2(x))$ that jointly solves equations (16), (19), (22), (23), (24), and (25) for this value of x (Step 1 in the Mathematica file). In Step 2, we plug this vector into equilibrium condition (18), and show that the condition holds if and only if x is a root of the polynomial

$$P(X) = -(1-\beta_f)(3-\beta_c-2\beta_f)+2(1-\beta_f)(3-2\beta_c-2\beta_f)X+\left(\beta_c(1-3\beta_f)+2\beta_f(2-\beta_f)\right)X^2.$$

We show that P is convex and satisfies $P(0) < 0$ and $P(1) > 0$ (Step 3). Therefore, there exists a unique $\hat{x} \in [0,1]$ such that $P(\hat{x}) = 0$. That $\hat{x}$ is the largest root of quadratic polynomial P. Therefore, there exists at most one stationary subgame-perfect equilibrium. Conversely, since the objective functions in (20) and (21) are strictly concave in p_1 and p_2, respectively, first-order conditions are sufficient for optimality. It follows that the profile of prices pinned down by $\hat{x}$ is a stationary subgame-perfect equilibrium, and the mixed subgame has a unique stationary subgame-perfect equilibrium.

We compute $\hat{x}$, $v_1(\hat{x})$, and $v_2(\hat{x})$ in Step 4. Recall that v_i is the value of firm i per free buyer. At stage 0, there is a mass 1 of free buyers. Therefore, v_i also gives us the present discounted value of firm i's profits at time 0. $\square$

A.2 The ETF game

Having fully characterized the equilibria in all subgames starting at time $t = 0$, we go back to stage -1 and solve for the equilibria of the ETF game. Firms choose between actions n (no ETF) and e (ETF). Let v_k^l denote the equilibrium profit of a firm that plays $k \in \{n, e\}$ when its rival plays $l \in \{n, e\}$. As shown in Section 2, $v_n^n = \frac{1}{1-\beta_f}\frac{1}{2}$ and $v_e^e = \frac{1-\beta_c}{1-\beta_f}\frac{1}{2}$. Moreover, v_e^n and v_n^e are as in Appendix A.1 (see Lemma 1). The following lemma characterizes best responses, and thus the set of pure-strategy equilibria, for this two-by-two game:

Lemma 2. *There exist functions $\beta_c^n, \beta_c^e :\ [0,1) \longrightarrow [0,1)$ such that for every $(\beta_c, \beta_f) \in [0,1)^2$,*

- *$v_n^n \geq v_e^n$ (resp. $v_n^n \leq v_e^n$) if and only if $\beta_c \geq \beta_c^n(\beta_f)$ (resp. $\beta_c \leq \beta_c^n(\beta_f)$),*
- *$v_e^e \geq v_n^e$ (resp. $v_e^e \leq v_n^e$) if and only if $\beta_c \leq \beta_c^e(\beta_f)$ (resp. $\beta_c \geq \beta_c^e(\beta_f)$).*

In addition, $\beta_c^n(0) = \beta_c^e(0) = 0$, and $\beta_c^n(\beta_f) < \beta_c^e(\beta_f)$ for every $\beta_f > 0$.

Proof. Details of the calculations can again be found in Mathematica file `ETF-Hotelling.nb`. We begin by studying the behavior of $v_n^n - v_e^n$. It is straightforward to check that, when $\beta_f = \beta_c = 0$, $v_e^n = \frac{1}{2} = v_n^n$. Moreover, $v_n^n > v_e^n$ whenever $\beta_c > \beta_f = 0$ (Step 5 in the Mathematica file). Therefore, $\beta_c^n(0) = 0$. In the following, we assume that $\beta_f > 0$. For every $\beta_f \in (0,1)$, define the quartic polynomial

$$\begin{aligned} P_{\beta_f}^n(X) = &\left(48\beta_f - 64\beta_f^2 + 16\beta_f^3 + 4\beta_f^4\right) + \left(-72 + 16\beta_f + 52\beta_f^2 - 20\beta_f^3\right) X \\ &+ \left(129 - 86\beta_f + 9\beta_f^2\right) X^2 + \left(-72 + 24\beta_f\right) X^3 + 16X^4. \end{aligned}$$

Using Mathematica (Step 6), we show that $v_n^n \geq v_e^n$ (resp. $v_n^n \leq v_e^n$) if and only if $\beta_c \geq \beta_c^n(\beta_f)$ (resp. $\beta_c \leq \beta_c^n(\beta_f)$), where $\beta_c^n(\beta_f)$ is equal to the first real root of polynomial $P_{\beta_f}(X)$ if $\beta_f \leq 9/10$, and to the second real root of that polynomial if $\beta_f > 9/10$.

Next, we turn to the behavior of $v_e^e - v_n^e$. As before, it is straightforward to check that, when $\beta_f = \beta_c = 0$, $v_n^e = \frac{1}{2} = v_e^e$. Moreover, $v_e^e < v_n^e$ whenever $\beta_c > \beta_f = 0$ (see Step 5). Therefore, $\beta_c^e(0) = 0$. In the following, we assume that $\beta_f > 0$. For every $\beta_f \in (0,1)$, define the polynomials

$$\begin{aligned} P_{\beta_f}^e(X) = \; &\left(-48\beta + 80\beta_f^2 - 32\beta_f^3 + 4\beta_f^2\right) + \left(72 - 80\beta_f + 12\beta_f^2 - 28\beta_f^3 + 8\beta_f^4\right) X \\ &+ \left(-87 + 98\beta_f + 9\beta_f^2 + 4\beta_f^4\right) X^2 + \left(30 - 28\beta_f - 14\beta_f^2 - 4\beta_f^3\right) X^3 \\ &+ \left(1 - 6\beta_f + 9\beta_f^2\right) X^4, \\ \text{and } Q(X) = \; &167 + 926X + 1079X^2 + 384X^3. \end{aligned}$$

Define $\beta_c^e(\beta_f)$ as the second real root of polynomial $P_{\beta_f}^e(X)$ when $\beta_f \neq 1/3$, and as minus the first real root of polynomial $Q(X)$ when $\beta_f = 1/3$. In Step 7, we show that $v_e^e \geq v_n^e$ (resp. $v_e^e \leq v_n^e$) if and only if $\beta_c \leq \beta_c^e(\beta_f)$ (resp. $\beta_c \geq \beta_c^e(\beta_f)$).

Finally, we show that the inequalities $v_n^n \leq v_e^n$ and $v_e^e \leq v_n^e$ cannot hold simultaneously when $\beta_f > 0$ (Step 8). It follows that $\beta_c^n(\beta_f) < \beta_c^e(\beta_f)$ for every $\beta_f > 0$. □

B Additional empirical results

B.1 Alternative specifications of the static demand model

Table 14 reports estimation results for the static demand model for various combinations of product, time, and carrier-time fixed effects. The specifications in columns (5)–(7) constrain the coefficients on p_{jt} and P_{jt} to be identical; those in columns (1)–(4) do not. The IV specifications in columns (2), (4), and (6) include all the instrumental variables described in

Section 5. The instrumental variables included in column (7) are average age and consumer satisfaction by products of competitors, as in our main specification of the dynamic model. Consistent with Table 2 in the main text, Table 14 suggests that OLS specifications suffer from an endogeneity bias, as the coefficients on p_{jt} and $p_{jt} + P_{jt}$ are estimated to be positive. Price coefficient estimates in all IV specifications are negative, as expected.

Table 14: Product (handset-carrier) fixed-effect regressions, 16,408 observations

parameters	unrestricted				restricted		
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) IV*
handset price, P_{jt}	-4.568	-21.033	-4.591	-15.565			
(s.e.)	(0.263)	(16.482)	(0.262)	(14.890)			
service fee, p_{jt}	1.085	-19.084	1.021	-17.273			
(s.e.)	(0.091)	(5.420)	(0.091)	(4.345)			
total cost, $p_{jt} + P_{jt}$					0.340	-17.190	-19.185
(s.e.)					(0.085)	(4.296)	(6.030)
constant	-6.632	2.945	-8.070	1.702	-8.148	1.787	2.757
(s.e.)	(0.066)	(2.719)	(0.046)	(2.216)	(0.046)	(2.092)	2.935
time fixed effect	yes	yes	no	no	no	no	no
handset fixed effect	no	no	no	no	no	no	no
product fixed effect	yes	yes	yes	yes	yes	yes	yes
carrier-time fixed effect	no	no	yes	yes	yes	yes	yes
first stage statistics							
F statistic, P_{jt}		44.68		11.76			
(p-value)		(0.000)		(0.000)			
F statistic, p_{jt}		54.20		14.34			
(p-value)		(0.000)		(0.000)			
F statistic, $P_{jt} + p_{jt}$						18.61	18.99
(p-value)						(0.000)	(0.000)

Notes: Regressions labeled "IV" are two-stage least squares with all 4 instrumental variables; regression "IV" has only 2 instruments: average age and consumer satisfaction by products of competitors.*

Table 15 reports estimation results for the static demand model using handset and carrier-time fixed effects. The specifications in columns (3)–(5) constrain the coefficients on p_{jt} and P_{jt} to be identical; those in columns (1) and (2) do not. The IV specifications in columns (2) and (4) include all the instrumental variables from Section 5; column (5) only uses average age and consumer satisfaction by products of competitors. Again, OLS specifications deliver positive coefficient estimates on service fee and total costs, whereas parameter estimates from IV specifications have the expected sign.

B.2 Summary statistics on carrier dummies

Below, we compare estimates for carrier-time dummy variables for the one-type and four-type versions of the structural model. Both models suggest a constant decline in the average quality of each carrier over time. This is consistent with improvements in the value of the outside option, which represents any *non-contract-based* telecommunication service. Table 16

Table 15: Handset fixed-effect regressions, 16,408 observations

parameters	unrestricted		restricted		
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) IV*
handset price, P_{jt}	-3.549	-4.592			
(s.e.)	(0.284)	(9.098)			
service fee, p_{jt}	1.397	-10.030			
(s.e.)	(0.102)	(2.968)			
total cost, $p_{jt} + P_{jt}$			0.755	-9.574	-9.121
(s.e.)			(0.094)	(2.846)	(3.195)
constant		1.191	-3.640	1.368	1.149
(s.e.)		(1.437)	(0.173)	(1.396)	(1.563)
time fixed effect	no	no	no	no	no
handset fixed effect	yes	yes	yes	yes	yes
product fixed effect	no	no	no	no	no
carrier-time fixed effect	yes	yes	yes	yes	yes
first stage statistics					
F statistic, P_{jt}		5.98			
(p-value)		(0.000)			
F statistic, p_{jt}		7.22			
(p-value)		(0.000)			
F statistic, $P_{jt} + p_{jt}$				6.58	10.03
(p-value)				(0.000)	(0.000)

Notes: Regressions labeled "IV" are two-stage least squares with all 4 instrumental variables; regression "IV" has only 2 instruments: average age and consumer satisfaction by products of competitors.*

provides summary statistics for the estimates. Overall, we find carrier-time effects in the two models are closely correlated with a correlation coefficient of 0.997. The heterogeneous-type model estimates slightly lower parameter values.

Table 16: Summary statistics for carrier-time effects for one- and four-type models

model	mean	median	min	max	s.d.
one-type	-2.46	-2.38	-5.28	0.00	1.23
four-type	-2.40	-2.32	-5.19	0.00	1.21

Table 17 reports correlations in estimated carrier-time dummies. Estimates of the average product quality appear to be closely correlated across carriers.

Table 17: Correlations in carrier-time effects for one- and four-type models

	one-type model					four-type model				
	ATT	OTH	SPR	TMO	VER	ATT	OTH	SPR	TMO	VER
ATT	1.00					1.00				
OTH	0.93	1.00				0.92	1.00			
SPR	0.98	0.97	1.00			0.98	0.97	1.00		
TMO	0.99	0.93	0.97	1.00		0.99	0.91	0.96	1.00	
VER	0.99	0.95	0.99	0.99	1.00	0.99	0.94	0.99	0.98	1.00

B.3 Robustness analysis: initial and terminal period conditions

Our main specification assumes all consumers hold the outside option at the beginning of period $t = 1$, while consumers believe handset prices, service fees, and mean flow utilities evolve according to an AR(1) process without innovation after the final sample period. In this appendix, we evaluate the quantitative implications of those assumptions. Estimation results for various robustness checks are reported in Tables 18 and 19:

- Column (1) replicates the baseline model from Table 3.
- In column (2), all consumers hold the outside option at the beginning of period $t = 1$ (as in our baseline model), but prices and quality levels are assumed to stay constant after period T.
- In columns (3) and (4), we assume that the wireless market emerged 15 periods before our sample. Pre- and post-sample prices and qualities are assumed to be random and multiplicative perturbations of their values at time $t = 1$ and $t = T$, respectively. Specifically, for $t < 1$ (resp. $t > T$), we have $p_{jt} = \chi^p_{jt} p_{j1}$, $P_{jt} = \chi^P_{jt} P_{j1}$, and $\delta_{jt} = \chi^\delta_{jt} \delta_{j1}$ (resp. $p_{jt} = \chi^p_{jt} p_{jT}$, $P_{jt} = \chi^P_{jt} P_{jT}$, and $\delta_{jt} = \chi^\delta_{jt} \delta_{jT}$), where the random variables χ are drawn i.i.d. across products and periods from a uniform distribution over $[0.5, 1.5]$. That is, pre- and post-sample prices and quality levels can differ from their values at $t = 1$ and $t = T$ by at most 50 percent. In column (3), we set $\chi^p_{jt} = \chi^P_{jt} = \chi^\delta_{jt}$, i.e., price and quality shocks are perfectly correlated within a product-time. Instead, in column (4), price and quality shocks are uncorrelated within a product-time.
- In columns (5) and (6), all consumers hold the outside option at the beginning of period $t = 1$, and post-sample prices and qualities are assumed to follow an AR(1) process with random innovation. In column (5), price and quality innovations are perfectly correlated within a product-time; in column (6), they are uncorrelated.
- In column (7), we assume that the wireless market emerged 15 periods before our sample. Pre- and post-sample prices and qualities follow an AR(1) process without innovation.
- In columns (8) and (9), we assume that the wireless market emerged 15 periods before our sample. Pre- and post-sample prices and qualities follow an AR(1) process with random innovation. In column (8), price and quality innovations are perfectly correlated within a product-time; in column (9), they are uncorrelated.

As mentioned in the main text, the estimation results differ little across the various specifications.

Table 18: Robustness checks on initial and terminal period conditions, 2nd stage GMM (1)

	(1)		(2)		(3)		(4)	
initial, t≤0 terminal, t>T	outside option AR(1) deterministic		outside option same as at T		at $t=1$ w. cor. shock at $t=T$ w. cor. shock		at $t=1$ w. unc. shock at $t=T$ w. unc. shock	
	coef	s.e.	coef	s.e.	coef	s.e.	coef	s.e.
price	-8.163	(3.014)	-8.582	(2.054)	-8.053	(2.887)	-8.208	(2.974)
const	2.217	(1.873)	1.852	(0.543)	2.112	(1.756)	2.189	(1.782)
ATT-2005h2	-0.390	(0.248)	0.138	(0.644)	-0.360	(0.244)	-0.348	(0.245)
ATT-2006h1	-0.704	(0.250)	-0.145	(0.669)	-0.671	(0.240)	-0.662	(0.237)
ATT-2006h2	-0.842	(0.235)	-0.274	(0.680)	-0.808	(0.223)	-0.800	(0.220)
ATT-2007h1	-0.939	(0.241)	-0.372	(0.666)	-0.904	(0.225)	-0.897	(0.220)
ATT-2007h2	-1.272	(0.250)	-0.707	(0.653)	-1.237	(0.230)	-1.231	(0.223)
ATT-2008h1	-1.477	(0.279)	-0.918	(0.623)	-1.439	(0.254)	-1.436	(0.243)
ATT-2008h2	-1.672	(0.308)	-1.119	(0.595)	-1.633	(0.278)	-1.632	(0.265)
ATT-2009h1	-1.835	(0.316)	-1.283	(0.588)	-1.795	(0.285)	-1.795	(0.272)
ATT-2009h2	-2.105	(0.346)	-1.558	(0.564)	-2.064	(0.312)	-2.066	(0.298)
ATT-2010h1	-2.194	(0.305)	-1.639	(0.596)	-2.154	(0.275)	-2.154	(0.262)
ATT-2010h2	-2.434	(0.323)	-1.883	(0.583)	-2.394	(0.291)	-2.395	(0.278)
ATT-2011h1	-2.703	(0.359)	-2.158	(0.555)	-2.661	(0.323)	-2.664	(0.310)
ATT-2011h2	-2.924	(0.381)	-2.382	(0.540)	-2.881	(0.343)	-2.885	(0.331)
ATT-2012h1	-3.117	(0.390)	-2.609	(0.532)	-3.244	(0.345)	-3.147	(0.505)
OTH-2005h1	-3.083	(0.353)	-2.838	(0.455)	-3.057	(0.339)	-3.056	(0.332)
OTH-2005h2	-2.890	(0.321)	-2.316	(0.696)	-2.852	(0.303)	-2.848	(0.297)
OTH-2006h1	-2.751	(0.309)	-2.183	(0.669)	-2.713	(0.287)	-2.710	(0.279)
OTH-2006h2	-2.865	(0.296)	-2.296	(0.668)	-2.828	(0.275)	-2.824	(0.267)
OTH-2007h1	-2.730	(0.288)	-2.163	(0.657)	-2.692	(0.264)	-2.689	(0.255)
OTH-2007h2	-3.133	(0.310)	-2.571	(0.633)	-3.094	(0.283)	-3.092	(0.272)
OTH-2008h1	-3.449	(0.356)	-2.897	(0.587)	-3.407	(0.322)	-3.409	(0.310)
OTH-2008h2	-3.639	(0.380)	-3.091	(0.565)	-3.596	(0.343)	-3.600	(0.331)
OTH-2009h1	-3.751	(0.382)	-3.204	(0.562)	-3.708	(0.346)	-3.711	(0.333)
OTH-2009h2	-4.095	(0.450)	-3.559	(0.516)	-4.050	(0.408)	-4.057	(0.395)
OTH-2010h1	-4.357	(0.428)	-3.818	(0.529)	-4.312	(0.388)	-4.319	(0.375)
OTH-2010h2	-5.061	(0.479)	-4.530	(0.494)	-5.014	(0.435)	-5.024	(0.422)
OTH-2011h1	-5.264	(0.504)	-4.737	(0.476)	-5.216	(0.458)	-5.227	(0.447)
OTH-2011h2	-5.240	(0.474)	-4.708	(0.496)	-5.193	(0.429)	-5.203	(0.418)
OTH-2012h1	-5.284	(0.477)	-4.784	(0.492)	-5.407	(0.425)	-5.316	(0.595)
SPR-2005h1	-0.484	(0.281)	-0.828	(0.465)	-0.550	(0.298)	-0.659	(0.362)
SPR-2005h2	-0.889	(0.284)	-0.463	(0.553)	-0.862	(0.278)	-0.864	(0.278)
SPR-2006h1	-0.923	(0.268)	-0.405	(0.631)	-0.889	(0.260)	-0.882	(0.259)
SPR-2006h2	-1.079	(0.259)	-0.530	(0.662)	-1.044	(0.249)	-1.035	(0.248)
SPR-2007h1	-1.296	(0.281)	-0.739	(0.654)	-1.259	(0.263)	-1.252	(0.257)
SPR-2007h2	-1.435	(0.270)	-0.872	(0.659)	-1.398	(0.252)	-1.391	(0.245)
SPR-2008h1	-1.601	(0.295)	-1.040	(0.642)	-1.563	(0.272)	-1.558	(0.262)
SPR-2008h2	-2.018	(0.346)	-1.465	(0.600)	-1.976	(0.315)	-1.976	(0.302)
SPR-2009h1	-2.183	(0.326)	-1.627	(0.616)	-2.143	(0.297)	-2.141	(0.285)
SPR-2009h2	-2.808	(0.413)	-2.267	(0.550)	-2.764	(0.375)	-2.768	(0.361)
SPR-2010h1	-2.977	(0.381)	-2.431	(0.573)	-2.934	(0.347)	-2.937	(0.333)
SPR-2010h2	-3.278	(0.405)	-2.735	(0.555)	-3.234	(0.368)	-3.238	(0.354)
SPR-2011h1	-3.690	(0.454)	-3.155	(0.520)	-3.644	(0.413)	-3.651	(0.399)
SPR-2011h2	-3.717	(0.426)	-3.177	(0.542)	-3.672	(0.387)	-3.678	(0.375)
SPR-2012h1	-3.882	(0.428)	-3.376	(0.537)	-4.007	(0.382)	-3.910	(0.536)
TMO-2005h1	-0.394	(0.340)	-0.299	(0.422)	-0.410	(0.333)	-0.401	(0.337)
TMO-2005h2	-0.663	(0.283)	-0.098	(0.745)	-0.635	(0.288)	-0.619	(0.298)
TMO-2006h1	-1.002	(0.291)	-0.404	(0.802)	-0.973	(0.295)	-0.957	(0.305)
TMO-2006h2	-1.219	(0.258)	-0.624	(0.775)	-1.188	(0.258)	-1.175	(0.264)
TMO-2007h1	-1.473	(0.247)	-0.883	(0.754)	-1.441	(0.243)	-1.430	(0.245)
TMO-2007h2	-1.584	(0.228)	-0.994	(0.751)	-1.552	(0.225)	-1.541	(0.228)
TMO-2008h1	-1.939	(0.252)	-1.361	(0.701)	-1.905	(0.238)	-1.897	(0.234)
TMO-2008h2	-2.044	(0.252)	-1.467	(0.692)	-2.009	(0.236)	-2.002	(0.231)
TMO-2009h1	-2.143	(0.257)	-1.567	(0.684)	-2.107	(0.240)	-2.101	(0.233)
TMO-2009h2	-2.224	(0.261)	-1.652	(0.668)	-2.188	(0.240)	-2.183	(0.232)
TMO-2010h1	-2.381	(0.261)	-1.809	(0.666)	-2.344	(0.240)	-2.339	(0.231)
TMO-2010h2	-2.700	(0.263)	-2.129	(0.663)	-2.664	(0.242)	-2.659	(0.233)
TMO-2011h1	-3.270	(0.317)	-2.709	(0.613)	-3.230	(0.287)	-3.230	(0.275)
TMO-2011h2	-3.213	(0.253)	-2.637	(0.681)	-3.177	(0.235)	-3.171	(0.229)
TMO-2012h1	-3.460	(0.252)	-2.918	(0.675)	-3.594	(0.230)	-3.487	(0.337)
VER-2005h1	-1.318	(0.312)	-1.373	(0.337)	-1.318	(0.309)	-1.356	(0.327)
VER-2005h2	-1.665	(0.333)	-1.141	(0.572)	-1.627	(0.309)	-1.627	(0.302)
VER-2006h1	-1.709	(0.328)	-1.158	(0.598)	-1.670	(0.301)	-1.669	(0.289)
VER-2006h2	-1.979	(0.330)	-1.423	(0.605)	-1.939	(0.301)	-1.938	(0.289)
VER-2007h1	-2.084	(0.332)	-1.527	(0.601)	-2.044	(0.301)	-2.043	(0.289)
VER-2007h2	-2.311	(0.357)	-1.757	(0.586)	-2.270	(0.323)	-2.271	(0.310)
VER-2008h1	-2.379	(0.373)	-1.827	(0.570)	-2.336	(0.338)	-2.338	(0.324)
VER-2008h2	-2.583	(0.411)	-2.038	(0.542)	-2.539	(0.373)	-2.544	(0.359)
VER-2009h1	-2.792	(0.415)	-2.247	(0.542)	-2.747	(0.376)	-2.752	(0.362)
VER-2009h2	-3.062	(0.426)	-2.519	(0.531)	-3.017	(0.386)	-3.023	(0.372)
VER-2010h1	-3.104	(0.393)	-2.556	(0.555)	-3.061	(0.355)	-3.064	(0.342)
VER-2010h2	-3.417	(0.411)	-2.872	(0.542)	-3.373	(0.372)	-3.377	(0.359)
VER-2011h1	-3.704	(0.431)	-3.163	(0.527)	-3.659	(0.390)	-3.665	(0.377)
VER-2011h2	-3.898	(0.458)	-3.360	(0.511)	-3.851	(0.415)	-3.859	(0.403)
VER-2012h1	-4.170	(0.480)	-3.669	(0.494)	-4.293	(0.429)	-4.200	(0.593)

Notes: Standard errors in parentheses. Specification (1) replicates the baseline model from Table 3. In specification (2), consumers initially hold the outside option and believe prices and flow utilities stay constant after period T. In specification (3) and (4), we simulate 15 periods of initial conditions using randomly perturbed prices and flow utilities from the first period of data, and assume that consumers believe the evolution of prices and quality levels after T is given by random perturbations of prices and flow utilities at T. Estimates in specifications (3) use correlated shocks for the prices and quality levels of the same product, while specification (4) allows the prices and quality levels of the same product to move independently.

Table 19: Robustness checks on initial and terminal period conditions, 2nd stage GMM (2)

	(5)		(6)		(7)		(8)		(9)	
initial, t≤0:	outside option		outside option		AR(1), deterministic		AR(1), cor. shocks		AR(1), unc. shocks	
terminal, t>T:	AR(1), cor. shocks		AR(1), unc. shocks		AR(1), deterministic		AR(1), cor. shocks		AR(1), unc. shocks	
	coef	(s.e.)	coef	(s.e.)	coef	(s.e.)	coef	(s.e.)	coef	(s.e.)
price	-8.594	(2.056)	-8.592	(2.056)	-8.111	(2.998)	-8.183	(3.211)	-8.061	(3.052)
constant	1.856	(0.539)	1.855	(0.540)	2.144	(1.806)	2.149	(1.835)	2.081	(1.791)
ATT-2005h2	0.142	(0.648)	0.141	(0.648)	-0.375	(0.246)	-0.348	(0.246)	-0.351	(0.243)
ATT-2006h1	-0.141	(0.674)	-0.142	(0.673)	-0.686	(0.243)	-0.657	(0.235)	-0.662	(0.234)
ATT-2006h2	-0.271	(0.685)	-0.271	(0.684)	-0.823	(0.227)	-0.795	(0.218)	-0.799	(0.217)
ATT-2007h1	-0.368	(0.671)	-0.369	(0.670)	-0.919	(0.231)	-0.891	(0.212)	-0.895	(0.215)
ATT-2007h2	-0.703	(0.658)	-0.704	(0.658)	-1.253	(0.238)	-1.225	(0.212)	-1.228	(0.218)
ATT-2008h1	-0.914	(0.628)	-0.915	(0.627)	-1.456	(0.264)	-1.430	(0.228)	-1.430	(0.237)
ATT-2008h2	-1.115	(0.600)	-1.116	(0.600)	-1.651	(0.291)	-1.626	(0.249)	-1.624	(0.260)
ATT-2009h1	-1.280	(0.593)	-1.280	(0.592)	-1.813	(0.299)	-1.789	(0.256)	-1.787	(0.267)
ATT-2009h2	-1.555	(0.569)	-1.556	(0.568)	-2.083	(0.328)	-2.059	(0.282)	-2.056	(0.293)
ATT-2010h1	-1.636	(0.602)	-1.637	(0.601)	-2.172	(0.288)	-2.147	(0.246)	-2.146	(0.257)
ATT-2010h2	-1.880	(0.588)	-1.881	(0.587)	-2.413	(0.306)	-2.388	(0.262)	-2.386	(0.272)
ATT-2011h1	-2.155	(0.560)	-2.156	(0.559)	-2.680	(0.340)	-2.657	(0.294)	-2.653	(0.306)
ATT-2011h2	-2.379	(0.545)	-2.380	(0.544)	-2.901	(0.362)	-2.878	(0.316)	-2.873	(0.325)
ATT-2012h1	-2.620	(0.544)	-2.603	(0.528)	-3.094	(0.371)	-3.176	(0.367)	-3.138	(0.379)
OTH-2005h1	-2.836	(0.457)	-2.837	(0.457)	-3.073	(0.344)	-3.052	(0.329)	-3.088	(0.337)
OTH-2005h2	-2.312	(0.701)	-2.313	(0.700)	-2.869	(0.310)	-2.843	(0.288)	-2.846	(0.293)
OTH-2006h1	-2.180	(0.674)	-2.180	(0.673)	-2.730	(0.295)	-2.704	(0.267)	-2.709	(0.277)
OTH-2006h2	-2.293	(0.673)	-2.294	(0.673)	-2.844	(0.282)	-2.818	(0.255)	-2.821	(0.262)
OTH-2007h1	-2.159	(0.662)	-2.160	(0.661)	-2.708	(0.273)	-2.683	(0.243)	-2.685	(0.251)
OTH-2007h2	-2.568	(0.638)	-2.569	(0.637)	-3.111	(0.294)	-3.086	(0.258)	-3.087	(0.268)
OTH-2008h1	-2.894	(0.592)	-2.895	(0.591)	-3.426	(0.337)	-3.403	(0.295)	-3.400	(0.306)
OTH-2008h2	-3.089	(0.569)	-3.089	(0.569)	-3.615	(0.360)	-3.593	(0.316)	-3.589	(0.327)
OTH-2009h1	-3.201	(0.567)	-3.202	(0.566)	-3.727	(0.363)	-3.705	(0.319)	-3.700	(0.329)
OTH-2009h2	-3.557	(0.520)	-3.557	(0.520)	-4.070	(0.428)	-4.050	(0.385)	-4.043	(0.393)
OTH-2010h1	-3.816	(0.534)	-3.816	(0.533)	-4.333	(0.407)	-4.312	(0.364)	-4.305	(0.373)
OTH-2010h2	-4.528	(0.499)	-4.528	(0.498)	-5.036	(0.457)	-5.017	(0.414)	-5.007	(0.421)
OTH-2011h1	-4.735	(0.480)	-4.736	(0.479)	-5.238	(0.482)	-5.220	(0.441)	-5.209	(0.447)
OTH-2011h2	-4.707	(0.500)	-4.707	(0.499)	-5.215	(0.452)	-5.196	(0.410)	-5.186	(0.416)
OTH-2012h1	-4.798	(0.502)	-4.780	(0.487)	-5.259	(0.455)	-5.345	(0.459)	-5.304	(0.468)
SPR-2005h1	-0.830	(0.466)	-0.830	(0.466)	-0.477	(0.278)	-0.506	(0.279)	-0.479	(0.276)
SPR-2005h2	-0.460	(0.557)	-0.461	(0.556)	-0.868	(0.278)	-0.852	(0.277)	-0.851	(0.275)
SPR-2006h1	-0.401	(0.635)	-0.402	(0.635)	-0.902	(0.261)	-0.881	(0.258)	-0.881	(0.256)
SPR-2006h2	-0.526	(0.667)	-0.527	(0.666)	-1.058	(0.251)	-1.036	(0.246)	-1.035	(0.245)
SPR-2007h1	-0.735	(0.659)	-0.736	(0.658)	-1.274	(0.268)	-1.253	(0.250)	-1.250	(0.253)
SPR-2007h2	-0.868	(0.664)	-0.869	(0.663)	-1.413	(0.257)	-1.392	(0.238)	-1.388	(0.241)
SPR-2008h1	-1.037	(0.647)	-1.038	(0.646)	-1.579	(0.279)	-1.558	(0.252)	-1.553	(0.256)
SPR-2008h2	-1.462	(0.605)	-1.463	(0.604)	-1.994	(0.327)	-1.975	(0.291)	-1.967	(0.297)
SPR-2009h1	-1.624	(0.622)	-1.624	(0.621)	-2.159	(0.308)	-2.140	(0.274)	-2.133	(0.279)
SPR-2009h2	-2.264	(0.555)	-2.265	(0.554)	-2.783	(0.391)	-2.766	(0.353)	-2.755	(0.357)
SPR-2010h1	-2.428	(0.578)	-2.428	(0.578)	-2.953	(0.361)	-2.935	(0.323)	-2.925	(0.328)
SPR-2010h2	-2.733	(0.560)	-2.733	(0.559)	-3.253	(0.384)	-3.236	(0.346)	-3.225	(0.350)
SPR-2011h1	-3.153	(0.525)	-3.154	(0.524)	-3.664	(0.431)	-3.648	(0.393)	-3.635	(0.396)
SPR-2011h2	-3.175	(0.546)	-3.176	(0.545)	-3.691	(0.404)	-3.675	(0.367)	-3.663	(0.369)
SPR-2012h1	-3.387	(0.550)	-3.370	(0.535)	-3.857	(0.406)	-3.944	(0.408)	-3.901	(0.414)
TMO-2005h1	-0.298	(0.424)	-0.299	(0.424)	-0.441	(0.334)	-0.442	(0.329)	-0.474	(0.343)
TMO-2005h2	-0.094	(0.749)	-0.095	(0.749)	-0.653	(0.283)	-0.623	(0.304)	-0.637	(0.288)
TMO-2006h1	-0.400	(0.807)	-0.401	(0.806)	-0.988	(0.292)	-0.953	(0.321)	-0.964	(0.305)
TMO-2006h2	-0.620	(0.780)	-0.621	(0.780)	-1.203	(0.258)	-1.170	(0.276)	-1.178	(0.265)
TMO-2007h1	-0.879	(0.759)	-0.880	(0.759)	-1.456	(0.244)	-1.425	(0.252)	-1.432	(0.245)
TMO-2007h2	-0.990	(0.756)	-0.991	(0.755)	-1.567	(0.225)	-1.536	(0.237)	-1.543	(0.228)
TMO-2008h1	-1.357	(0.706)	-1.358	(0.706)	-1.921	(0.244)	-1.891	(0.228)	-1.895	(0.230)
TMO-2008h2	-1.464	(0.698)	-1.464	(0.697)	-2.026	(0.242)	-1.996	(0.224)	-2.000	(0.227)
TMO-2009h1	-1.564	(0.689)	-1.565	(0.688)	-2.123	(0.247)	-2.095	(0.225)	-2.098	(0.229)
TMO-2009h2	-1.649	(0.673)	-1.650	(0.672)	-2.205	(0.249)	-2.177	(0.221)	-2.179	(0.227)
TMO-2010h1	-1.806	(0.671)	-1.806	(0.670)	-2.361	(0.249)	-2.333	(0.220)	-2.335	(0.226)
TMO-2010h2	-2.126	(0.668)	-2.127	(0.667)	-2.681	(0.251)	-2.653	(0.221)	-2.655	(0.228)
TMO-2011h1	-2.707	(0.617)	-2.707	(0.616)	-3.249	(0.301)	-3.223	(0.259)	-3.222	(0.270)
TMO-2011h2	-2.635	(0.685)	-2.635	(0.684)	-3.193	(0.243)	-3.165	(0.219)	-3.168	(0.224)
TMO-2012h1	-2.929	(0.688)	-2.911	(0.673)	-3.441	(0.241)	-3.517	(0.231)	-3.489	(0.242)
VER-2005h1	-1.374	(0.338)	-1.374	(0.338)	-1.309	(0.304)	-1.323	(0.304)	-1.311	(0.309)
VER-2005h2	-1.138	(0.577)	-1.138	(0.576)	-1.642	(0.317)	-1.625	(0.293)	-1.621	(0.298)
VER-2006h1	-1.155	(0.603)	-1.156	(0.602)	-1.687	(0.312)	-1.668	(0.281)	-1.662	(0.285)
VER-2006h2	-1.420	(0.610)	-1.421	(0.609)	-1.957	(0.313)	-1.935	(0.278)	-1.932	(0.285)
VER-2007h1	-1.524	(0.606)	-1.524	(0.605)	-2.061	(0.314)	-2.039	(0.276)	-2.036	(0.285)
VER-2007h2	-1.754	(0.591)	-1.755	(0.590)	-2.288	(0.337)	-2.266	(0.298)	-2.262	(0.307)
VER-2008h1	-1.824	(0.575)	-1.825	(0.574)	-2.355	(0.353)	-2.334	(0.312)	-2.329	(0.321)
VER-2008h2	-2.035	(0.547)	-2.036	(0.546)	-2.559	(0.390)	-2.539	(0.348)	-2.532	(0.357)
VER-2009h1	-2.244	(0.547)	-2.245	(0.546)	-2.767	(0.394)	-2.747	(0.352)	-2.740	(0.360)
VER-2009h2	-2.517	(0.536)	-2.518	(0.535)	-3.037	(0.405)	-3.018	(0.363)	-3.010	(0.370)
VER-2010h1	-2.553	(0.560)	-2.554	(0.559)	-3.080	(0.372)	-3.059	(0.330)	-3.053	(0.339)
VER-2010h2	-2.869	(0.547)	-2.870	(0.546)	-3.392	(0.390)	-3.372	(0.348)	-3.365	(0.356)
VER-2011h1	-3.160	(0.532)	-3.161	(0.531)	-3.679	(0.409)	-3.660	(0.367)	-3.652	(0.375)
VER-2011h2	-3.358	(0.516)	-3.358	(0.515)	-3.872	(0.436)	-3.854	(0.395)	-3.844	(0.401)
VER-2012h1	-3.680	(0.507)	-3.663	(0.491)	-4.144	(0.457)	-4.231	(0.462)	-4.189	(0.469)

Notes: In specification (5), consumers initially hold the outside option and believe that, after T, quality and prices evolve according to an AR(1) process with correlated random innovations; specification (6) uses uncorrelated random innovations instead. In specification (7), quality and prices before $t = 1$ and after $t = T$ evolve according to an AR(1) process without innovations. Specification (8) adds correlated innovations to those AR(1) processes; in specification (9) innovations are uncorrelated.

B.4 Results for alternative sets of instrumental variables

Table 20 reports estimation results for three specifications of the one-type dynamic demand model. Specification (1) employs all the instrumental variables from Section 5. Specification (2) uses total number (IV1), average age (IV2), and consumer satisfaction (IV3) by products of competitors. Specification (3) includes IV2 and IV3 only. The overidentifying restrictions test does not reject any of the specifications in Table 3, and all parameter estimates are significant at the 1-percent level. Due to the relatively large standard errors, the t-test rejects statistically significant differences in the parameter estimates across the various specifications. Specifically, the t-statistic for the difference between (1) and (2) has a p-value of 0.69; when comparing (1) vs. (3) and (2) vs. (3), the p-values are 0.42 and 0.65, respectively.[30] As discussed in the main text, we elected to use specification (3) as our main specification because it is the one that gives rise to the smallest share of products with negative marginal cost estimates (see Section 7.2).

Table 20: Second-stage optimal GMM parameter estimates and elasticity predictions

parameter	estimates		
	(1)	(2)	(3)
price coefficient, α_p	-5.428	-6.466	-8.163
(s.e.)	(1.496)	(2.155)	(3.014)
carrier-time fixed effects	yes	yes	yes
handset fixed effects	yes	yes	yes
service fee elasticity			
average	-1.973	-2.350	-2.967
median	-2.017	-2.403	-3.033
standard deviation	0.557	0.663	0.838
handset price elasticity			
average	-0.350	-0.416	-0.524
median	-0.274	-0.326	-0.410
standard deviation	0.270	0.321	0.404
Hansen's J-stat	3.033	2.164	0.841
(p-value)	(0.386)	(0.339)	(0.359)

Notes: (1) employs IV1–IV4; (2) uses IV1–IV3; (3) uses IV2 and IV3.

Figures 10 and 11 reports histograms for service fee and handset own price elasticities for specifications (1) and (2), respectively. Naturally, those specifications give rise to lower elasticities (in absolute value) due to the lower price-coefficient estimate.

Tables 21 and 22 report results for our partial-equilibrium counterfactual simulations for specifications (1) and (2) of the one-type model. (See the first paragraph of Section 7.1 for a description of what each counterfactual simulation does.) Relative to our main specification,

[30] The t-test is computed assuming zero covariance between the coefficients.

Figure 10: Distribution of own price elasticity for all products, specification (1)

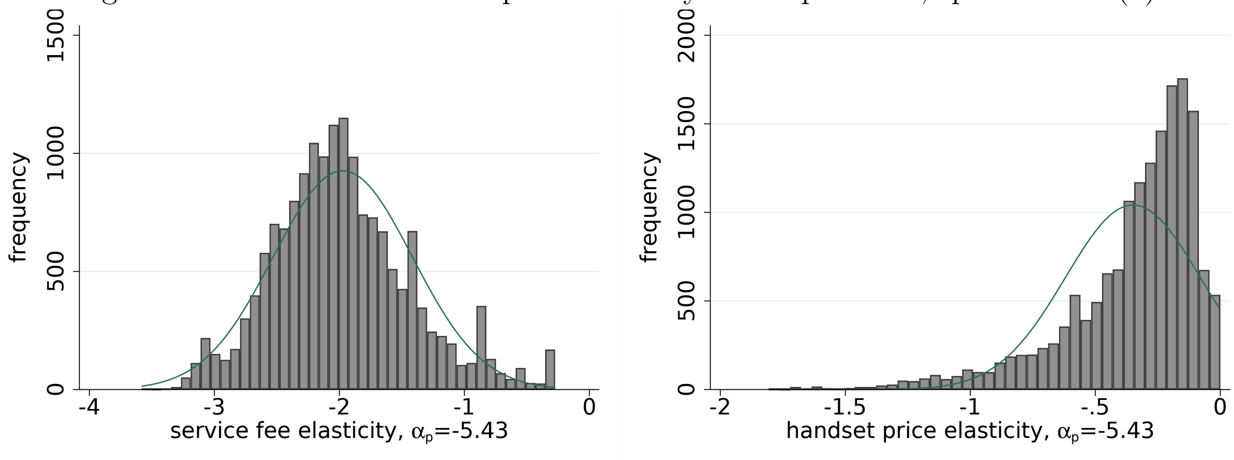
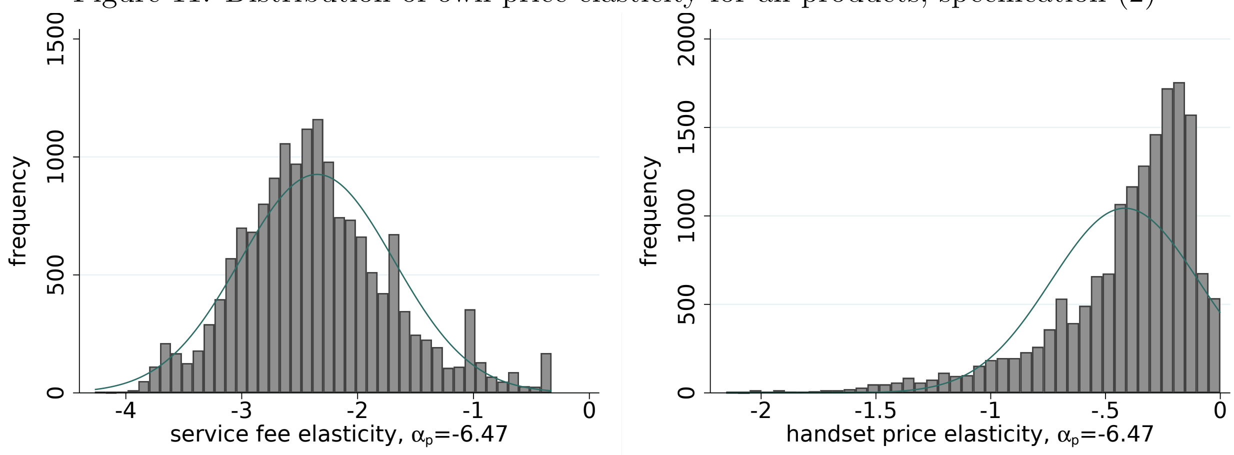


Figure 11: Distribution of own price elasticity for all products, specification (2)



due to the lower price-coefficient estimates, specifications (1) and (2) suggest smaller consumer welfare gains (compare Tables 21 and 22 to Table 6).

Table 23 reports the compensating changes in service fees that would offset the consumer-surplus gains from ETF elimination for all three specifications of the one-type model. Since the price-coefficient estimate is lower for specifications (1) and (2) than for our main specification (3), the compensating service fee increase is higher.

Table 21: Changes in consumer welfare and market shares, one-type model (1)

counterfactual scenario		mean	p50	min	max	sd
ETFs	handset	change in value functions				
No	purchased at obs. prices	0.44	0.43	0.39	0.55	0.03
No	purchased at new prices	0.27	0.26	0.20	0.38	0.03
No	rented	0.66	0.64	0.59	0.78	0.03
Yes	rented	0.12	0.12	0.10	0.13	0.01
ETFs	handset	change in market shares				
No	purchased at obs. prices	0.35	0.33	-0.59	1.27	0.21
No	purchased at new prices	0.49	0.50	-0.74	2.14	0.37
No	rented	0.50	0.36	-0.72	7.11	0.57
Yes	rented	0.19	0.09	-0.45	3.38	0.36

Notes: Service fees are held fixed; changes are percentage changes relative to the factual outcome.

Table 22: Changes in consumer welfare and market shares, one-type model (2)

counterfactual scenario		mean	p50	min	max	sd
ETFs	handset	change in value functions				
No	purchased at obs. prices	0.56	0.54	0.49	0.70	0.04
No	purchased at new prices	0.34	0.33	0.26	0.48	0.03
No	rented	0.84	0.82	0.74	1.01	0.04
Yes	rented	0.14	0.14	0.12	0.16	0.01
ETFs	handset	change in market shares				
No	purchased at obs. prices	0.40	0.37	-0.67	1.60	0.27
No	purchased at new prices	0.55	0.56	-0.81	2.75	0.46
No	rented	0.57	0.39	-0.79	10.40	0.74
Yes	rented	0.23	0.10	-0.51	4.77	0.47

Notes: Service fees are held fixed; changes are percentage changes relative to the factual outcome.

Table 23: Change in service fees offsetting consumer gains from ETF elimination, %

type of compensating change	spec.(3) $\alpha_p = -8.16$	spec.(2) $\alpha_p = -6.47$	spec.(1) $\alpha_p = -5.43$
increase in service fees at obs. h-set prices	42.59	43.09	43.38
increase in service fees at new h-set prices	31.70	31.36	31.12

Notes: Offsetting price increase is computed such that the difference between consumer value functions before the ETF elimination and consumer value functions after the ETF elimination with corresponding proportional change in service fees is zero on average.

B.5 Partial equilibrium counterfactuals for the four-type model

Table 24 reports results for our partial-equilibrium counterfactual simulations for the four-type model. (See the first paragraph of Section 7.1 for a description of what each counterfactual simulation does.) Relative to the one-type model, the four-type model, due to its slightly higher estimated price sensitivity, suggests larger gains in each of the counterfactual scenarios (compare Tables 6 and 24).

Table 24: Changes in consumer welfare and market shares, four-type model

counterfactual scenario		mean	p50	min	max	sd
ETFs	handset	change in value functions				
No	purchased at obs. prices	0.90	1.05	0.22	1.86	0.39
No	purchased at new prices	0.58	0.69	0.15	1.29	0.26
No	rented	1.41	1.69	0.30	2.98	0.64
Yes	rented	0.22	0.26	0.08	0.35	0.09
ETFs	handset	change in market shares				
No	purchased at obs. prices	0.81	0.51	-0.84	10.74	1.09
No	purchased at new prices	1.01	0.51	-0.95	20.64	1.60
No	rented	1.48	0.46	-0.93	235.87	3.89
Yes	rented	0.56	0.15	-0.71	41.96	1.56

Notes: Service fees are held fixed; changes are percentage changes relative to the factual outcome.