Pricing and Entry Incentives with Exclusive Contracts:

Evidence from Smartphones

Michael Sinkinson*

Harvard University

First Version: March, 2011

This Version: November, 2011

Abstract

I study the motivations for and implications of exclusive contracts, with an application to smartphones. Why would Apple choose to distribute its smartphone through only one carrier, and why would AT&T bid the most for exclusivity? I develop a model which shows that if upstream handset manufacturers face a relatively low price elasticity for their good compared to downstream wireless carriers, exclusive contracts can maximize their joint profits. An exclusive contract reduces price competition in the final good market but also increases returns to innovation for parties outside the contract, such as Google's Android. Different price elasticities among downstream firms due to network quality differences lead to different valuations of the exclusive contract. I estimate the relative elasticities of smartphone and carrier demand using simulation and MCMC methods on a detailed monthly dataset of consumer decisions over 2008-2010. Counterfactual simulations show the importance of recomputing the price equilibrium to understanding the observed market structure. Accounting for price effects, AT&T had the highest value of exclusivity with Apple, and was willing to compensate Apple $148 per unit sale foregone. Apple's exclusivity increased entry incentives for Android handset makers by approximately $1B.

JEL classification: L11, L14, L96,

Keywords: exclusive contracts, vertical contracting, mobile telecommunications, markov chain monte carlo

*The author would like to acknowledge the valuable advice and suggestions provided by Ariel Pakes, Guido Imbens, Greg Lewis, Bharat Anand, Julie Mortimer, John Asker, Andrei Shleifer, Matthew Gentzkow, Jesse Shapiro, and workshop participants at Harvard University. This research was funded in part by the Social Sciences and Humanities Research Council of Canada and the computations in this paper were run on the Odyssey cluster supported by the FAS Sciences Division Research Computing Group. E-mail: msinkins@fas.harvard.edu.

1 Introduction

A final good in the smartphone market consists of both a smartphone handset and the wireless service that enables it to function. Exclusive contracts in this market between upstream firms (handset manufacturers) and downstream firms (wireless carriers) are common.[1] Perhaps the most well-known is the contract between Apple and AT&T, which saw the former's iPhone handset exclusively available on AT&T's network in the United States. An exclusive contract such as this restricts Apple from engaging in trade with competing wireless carriers, and so the contract must compensate Apple for the lost market potential. Early models of exclusive contracts argued that such arrangements must be efficient, as AT&T would only be willing to sufficiently compensate Apple for the lost sales if the exclusive arrangement was efficient.[2] However, later approaches showed that such arrangements could lead to inefficient outcomes, such as the foreclosure of entry (Aghion & Bolton, 1987). While these contracts may have anti-competitive effects, they have also been shown to be pro-competitive in some settings, such as for protecting investments and addressing externalities (Bernheim & Whinston, 1998; Segal & Whinston, 2000).[3] Indeed, courts in the United States evaluate non-price vertical restraints under the Rule of Reason, instead of declaring them to be illegal *per se*.[4]

This paper proposes a simple motivation for exclusivity in the mobile telecommunications market based on the relative substitutability of the upstream goods (handsets) versus the downstream goods (wireless service). If the downstream goods are near-perfect substitutes, then downstream firms face high price elasticities for their goods and are only able to charge low markups above marginal cost for their goods in equilibrium. If the upstream goods are poor substitutes, those firms face low price elasticities and are able to charge large markups over marginal cost in equilibrium. I show that in such a setting, an exclusive contract can maximize the joint profits of the contracting parties by reducing price competition in the final goods market. However, these contracts also increase incentives for new upstream firms to enter. Finally, I investigate the willingness to pay of differentiated downstream firms, and find that firms with lower quality goods may be willing to bid the most for an exclusive contract as they have more to lose from a rival gaining exclusivity.

Apple launched its first ever smartphone in 2007, the iPhone, exclusively on AT&T (then Cingular) in the United States. Many handsets are released exclusively, although the Apple arrange-

[1] For example, in Consumer Reports' 2009 annual review of smartphones, 6 of the 10 devices that were rated as "Recommended" were exclusive to one of the four major US wireless carriers (Consumers Union of United States, 2009).

[2] These arguments, referred to as the Chicago School approach to this topic, are articulated in Posner (1976) and Bork (1978).

[3] See Katz (1989) for a survey of the literature on vertical contracts.

[4] Continental Television v. GTE Sylvania, 433 U.S. 36 (1977)

ment was notable for its 5 year term.[5] The popular press devoted much attention to the wisdom of the Apple decision, as AT&T was plagued by complaints of poor network quality with the iPhone, despite being the largest carrier in the US at the time.[6] In addition, many customers of other wireless carriers expressed interest in purchasing an iPhone, but could not do so without switching carriers. This led to political and regulatory attention being paid to exclusive contracts between handset makers and wireless networks. The Federal Communications Commission (FCC) and United States Senate have held hearings on the potentially negative impact on consumers of these arrangements.[7] The view of the major wireless carriers was that these arrangements increased welfare through greater incentives for innovation, as wireless carriers have a stronger incentive to invest in new innovations for which they will be the exclusive provider.[8] The view of consumer groups was that exclusivity leads welfare losses from higher prices and fewer choices for consumers.[9] Indeed, the effect on welfare is ambiguous.[10]

Some alternative mechanisms have been put forward to explain Apple's choice to enter into an exclusive contract. A first such argument was that Apple had a limited supply capacity: this was their first mobile phone, and so they were concerned that they could not meet demand if they launched on all carriers. However, if this were the case, it is unlikely that they would then have entered into a 5-year exclusive contract. Apple launched the iPhone globally less than 6 months after the initial US launch, indicating that any supply issues were short-term. A second argument was that exclusivity was essential to guarantee carrier investments in network technologies to support the iPhone. However, this argument was specifically rejected by the French competition authorities when they prematurely ended Apple's exclusive contract in that country. The exclusive carrier there was unable to show a significant investment that needed to be protected.[11]

[5]For example, the Palm Pre smartphones launched exclusively on Sprint, while the first touchscreen Blackberry was exclusive to Verizon and the first Blackberry Pearl exclusive to T-Mobile. Exclusive contracts are typically in the 6-12 month range.

[6]Apple Press Release "Apple Reinvents the Phone with iPhone," http://www.apple.com/pr/library/2007/01/09Apple-Reinvents-the-Phone-with-iPhone.html

[7]See Press Release, "Kerry, Wicker, Dorgan, Klobuchar Call for Increased Choice for Wireless Consumers", Sen. John Kerry, Jun 15, 2009.

[8]AT&T gave its "visual voicemail" feature for the iPhone as an example of such an investment. However, other carriers subsequently added this capability to their networks for handsets running Windows Mobile, Blackberry, Android, and Symbian operating systems.

[9]A specific concern was that, at the time, AT&T did not have a wireless network in several rural areas as well as the states of Vermont and Alaska. Consumers in those areas could not purchase an iPhone even if they were willing to switch carriers.

[10]This paper will not provide an estimate of the welfare effect of allowing exclusive contracts. There are two competing forces affecting welfare: higher prices in a static context, but increased entry in the dynamic context. While the effect of exclusive contracts on entry incentives can be measured, the change in entry probability is not identified, and so the latter force cannot be estimated. I can provide bounds on the latter force, but they are not informative for setting policy. For a paper that focuses on the welfare question of Apple's exclusivity, see Zhu, Liu & Chintagunta (2011).

[11]Conseil de la concurrence: Décision n° 08-MC-01 du 17 décembre 2008 relative à des pratiques mises en oeuvre

This paper begins with a theoretical analysis of firm decisions before moving into an empirical analysis and counterfactual simulations. The theory model builds on the approach taken by Rey & Stiglitz (1995), which shows that upstream competition can lead to exclusive contracts with undifferentiated downstream firms if the upstream goods are imperfect substitutes and prices are strategic complements.[12] The mechanism is that exclusivity decreases the interbrand price competition among upstream firms. This is more closely related to the setting at hand, as handsets are horizontally differentiated. However, the result also relies on the downstream firms being perfect substitutes and having no market power. This paper contributes a more general model that allows for downstream horizontal differentiation. I find that when upstream demand is relatively less sensitive to price than downstream demand, exclusive contracts can lessen price competition and overcome the losses associated with being available with fewer downstream firms. Furthermore, if downstream firms face different price elasticities for their goods, their willingness to pay for exclusivity will differ. I show that if consumers are willing to substitute between handset and network quality, a lower quality carrier may benefit more from an exclusive contract. Finally, I show that the existence of exclusive contracts can increase entry incentives for parties outside of the contract.

In order to estimate the magnitudes of these competing forces, we require estimates of the price elasticities of the various handsets and wireless carriers. However, estimating demand in such a setting poses several challenges. Demand is dependent between months as this is a durable good where a consumer's current demand is a function of the consumer's current "state" (her current handset, contract status with her wireless carrier, and any switching costs that her contract imposes). A consumer's state evolves according to a known process and the consumer's history of choices. I build a choice model closely related to the Pure Characteristics Model of Berry and Pakes (2007), where random coefficients rationalize decisions and individual tastes are invariant over time. Consumers will choose between bundles every period by comparing discounted future utility flows conditional on their current state. I avoid a fully-dynamic sequential model by simplifying consumer beliefs, and argue that the simplification is supported by the data.[13] Advantages of my approach are that I avoid i.i.d. taste shocks for every product in every period. I contrast my approach with a standard Logit demand model in Appendix E.

The econometric approach taken in this paper follows a simulated non-linear least squares (SNLLS) estimator developed by Laffont, Ossard and Vuong (1995), which explicitly corrects for

dans la distribution des iPhones.

[12] If the prices of two firms' products are strategic complements, then an increase in the price of one good gives the other firm an incentive to increase the price of the other good as well.

[13] An important contribution to the dynamic discrete choice literature is Gowrisankaran and Rysman (2011), which nests a demand system within a dynamic optimization decision framework, fully internalizing for a consumer the decision to buy now or wait. An example of a prior paper which avoids dynamic programming in such a setting is Geweke & Keane (1996).

simulation bias introduced by simulation methods. This estimator is feasible for a small set of markets, but as the number of parameters grows, it becomes computationally challenging. To estimate the full model, the SNLLS estimator is nested inside an MCMC routine developed by Chernozhukov and Hong (2003), enabling the estimation of a large number of unobserved heterogeneity terms that are not recoverable via an inversion mapping, as is common in demand estimation.

This paper's contributions to the literature are an extension of the theoretical understanding of exclusive contracting to the case of horizontal differentiation at both the upstream and downstream levels and an empirical investigation of such a setting, where magnitudes of the competing forces are estimated. Empirical applications of vertical exclusivity models are limited; for examples see Asker (2005) and Lee (2010). This paper's setting is an advantageous one in which to study the effect of downstream market power, as upstream goods are bundled one-to-one with the downstream good. The goal of the econometric analysis is to understand the the impact of consumer preferences on the observed vertical structure of an important market in the United States. The results from the econometric analysis are then used to answer three counterfactual questions: first, how much would each of the carriers have been willing to pay for exclusivity with Apple in 2007? Second, did Apple's exclusivity with AT&T increase entry incentives for Android handset makers, and if so, by how much? Finally, how much was AT&T willing to compensate Apple for each unit sale foregone due to exclusivity? Of particular interest is that the answer to the first of these questions is highly dependent on recomputing a price equilibrium. That is, if a new price equilibrium is not computed, the observed market outcome appears inefficient.

The paper proceeds as follows: Section 2 develops a theoretical model for the choice of vertical contracts in this setting. Section 3 describes the industry and data I will use for the empirical analysis. Section 4 develops an econometric model of consumer choices. Section 5 discusses the results from estimation. Section 6 provides the results from counterfactual simulations. Section 7 summarizes. All proofs are found in the Appendix.

2 A Theoretical Model of Upstream Entrant Decisions

The setting in question is one where upstream firms (say, handset manufacturers) sell a good to downstream firms (say, wireless carriers), who bundle this good with their own product and sell the final bundle to consumers. While models of vertical settings are common in economic theory, most models are limited to "triangular" market structures, with either one upstream firm and two downstream firms, or vice versa.[14] This section begins with an example where downstream goods

[14]Whinston (2006) notes this and further states that most markets in reality have multiple participants at each level. One exception is Besanko & Perry (1994), which has two upstream firms and multiple downstream firms spatially differentiated as in a Salop circle model. However, the contracts are restricted to be linear and an exclusive contract in

are homogenous to illustrate the static incentive for exclusive contracts in a simplified setting. Specifically, exclusive contracts lead to steeper reaction functions for the upstream firms, resulting in higher prices in equilibrium. The model is then generalized to allow for differentiated goods at both levels, to match the reality of the US mobile telecommunications industry and establish the main theoretical results. The main findings are that exclusivity is optimal when the downstream goods are good substitutes for one another, that exclusive contracts can lead to entry that would not be profitable in their absence, and that the value of the exclusive contract to a downstream firm depends on whether consumers are willing to substitute between quality of the upstream and downstream goods.

The specific terms of vertical contracts are unobserved in the mobile telecommunications sector, and so I wish to abstract away from bargaining over surplus between the contract parties. Instead I look at the joint surplus of the contracting parties as the determinant of the market structure. This is consistent with other research on exclusivity, such as Bernheim & Whinston (1998).[15,16] I will refer to the case of non-exclusivity as *common agency*, denoted by C below, the case of single-firm exclusivity as E, and of all upstream firms exclusive by EE.

2.1 An Example

An important distinction in this setting is the fact that a new smartphone is an imperfect substitute for an existing one; that is, while a given consumer may prefer an iPhone to, say, a Blackberry, there exists a set of prices at which the consumer would prefer the Blackberry. This imperfect competition allows for a static motivation for exclusive contracts.

Consider a simplified static setup (see Appendix C for all derivations): Firm A could invest K to develop a new smartphone. If it enters the market, it would have a smartphone with quality δ_A and marginal cost c, that would compete against Firm B that produces a smartphone with quality δ_B at marginal cost c. Consumer tastes for smartphones are as in a standard Hotelling model where consumers are distributed uniformly over an interval of length 1, with tastes for each smartphone for consumer i at location θ_i given by:

$$\begin{aligned} u_{Ai} &= \delta_A - p_A - \theta_i \\ u_{Bi} &= \delta_B - p_B - (1 - \theta_i) \end{aligned}$$

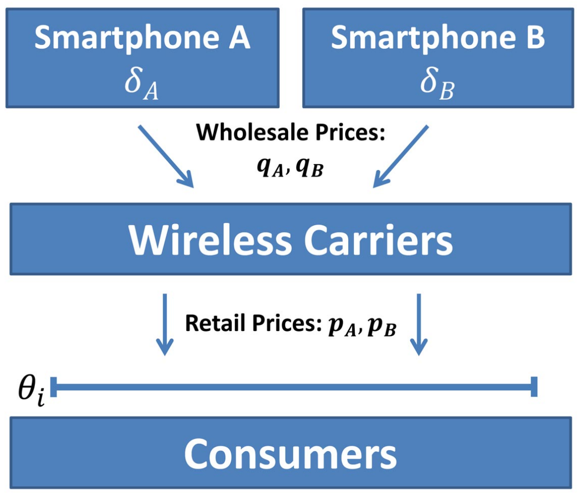
their setting only restricts the upstream competitor from every 2nd downstream firm.

[15] The first principle from Bernheim & Whinston's analysis of manufacturers and exclusive retailers: "the form of representation (exclusivity or common representation) that arises in equilibrium maximizes the joint surplus of the manufacturers and the retailer, subject to whatever inefficiencies may (or may not) characterize incentive contracting between the retailer and the manufacturers."

[16] To this end, I will allow for flexible contracts so that classic results such as double-marginalization are not an issue.

The smartphones are purchased from the manufacturers at wholesale prices q_A and q_B by N identical wireless carriers. These carriers compete in the downstream market by bundling the devices with their homogenous wireless networks that have marginal cost of zero, and selling the handset-network bundle to consumers at prices p_A and p_B. See Figure 1 for a diagram of this setup. Appendix C, shows the derivation of final consumer demand as a function of prices, $D^A(p_A, p_B)$ and $D^B(p_A, p_B)$, by locating the indifferent consumer and using the properties of the uniform distribution, as is standard for a Hotelling setup.

Figure 1: Hotelling Model



Firm A could choose to sell its handset to all carriers, or limit itself to a single exclusive carrier. I will first hold Firm B's choice fixed at non-exclusivity for now, but will revisit Firm B's choice at the end. I begin by analyzing Firm A's expected profits from common-agency, followed by the profits from exclusivity. The order of moves for this full-information setup is (1) upstream firms simultaneously choose wholesale prices, (2) carriers simultaneously choose retail prices, and (3) the market is realized.[17]

If no exclusive contracts are permitted, then all carriers will offer a bundle with each smartphone, and Bertrand competition will ensure that markups are competed to zero. Knowing this, the smartphone firms will choose wholesale prices in equilibrium to maximize their profits given that the downstream firms will not charge a markup:

$$\begin{aligned}
\pi_A^c &= (q_A - c)\, D^A(q_A, q_B) \\
\pi_B^c &= (q_B - c)\, D^B(q_A, q_B)
\end{aligned}$$

[17]Given the full-information setup of the game, the sequential nature merely facilitates exposition.

Assuming an interior solution,[18] the equilibrium wholesale price and profits for firm A if it enters with no exclusive arrangement are π_A^{C*}, shown in Table 1 with the resulting retail price. This is identical to the level profits earned if the two smartphone firms competed directly for consumers, due to Bertrand competition among the homogenous carriers.

Now suppose that Firm A could instead sign an agreement with one carrier guaranteeing exclusivity: Firm A could not sell its smartphone to any other carrier, but the carrier would be free to offer smartphone B. This is more closely aligned with the concept of "exclusive territories" than "exclusive contracts" in the literature (Katz, 1989). In this case, Firm A would expect its exclusive wireless carrier w to choose a retail price to maximize profits, where the carrier's profits and optimal retail price are given by:

$$\begin{aligned}\pi_w^E &= (p_A - q_A)\, D^A(p_A, q_B) \\ p_A^{E*} &= \left(\frac{1+\delta_A-\delta_B+p_B+q_A}{2}\right)\end{aligned}$$

The upstream firms choose wholesale prices knowing this markup. Upstream profits[19] are now

$$\begin{aligned}\pi_A^E &= \left(p_A^{E*}(q_A, q_B) - c\right) D^A\left(p_A^{E*}(q_A, q_B), q_B\right) \\ \pi_B^E &= (q_B - c)\, D^B\left(p_A^{E*}(q_A, q_B), q_B\right)\end{aligned}$$

Solving for equilibrium wholesale prices, we see that Firm B reaction function now takes the downstream optimization into account, and so is more inelastic with respect to Firm A's wholesale price. Consequently, both smartphones have higher prices over the range of interior solutions. Firm A's profit under exclusivity π_A^{E*}, is greater than its profits under common agency.

If Firm B were also exclusive, both firms would internalize the downstream pricing behavior, and Firm A's profits from exclusivity would rise further. Table 1 summarizes the outcomes of this setup.

Table 1: Equilibrium Outcomes of Hotelling Model

Form of Representation	Retail Price, A	Profits, Firm A
Common Agency (C)	$c+1+\frac{1}{3}(\delta_A-\delta_B)$	$\frac{1}{18}(3+\delta_A-\delta_B)^2$
A Exclusive (E)	$c+\frac{5}{4}+\frac{1}{4}(\delta_A-\delta_B)$	$\frac{1}{32}(5+\delta_A-\delta_B)^2$
A, B Exclusive (EE)	$c+2+\frac{2}{5}(\delta_A-\delta_B)$	$\frac{1}{25}(5+\delta_A-\delta_B)^2$

We may now draw a few conclusions from this model:

[18] Interior refers to the case where δ^A and δ^B are such that neither firm captures the entire market in equilibrium.

[19] Note that Firm A's profits include the downstream firm's markup. It is assumed that when exclusive, upstream firms are able to extract the full surplus via a fixed fee in a two-part tariff.

1. Firm A will earn greater profits under exclusivity. This result is not particularly novel: Rey and Stiglitz (1995) proved this in the setting of producers and retailers for a general quasi-concave profit function where $\delta_A = \delta_B$ and both upstream firms move simultaneously. Their Proposition 3 states that if retail prices are strategic complements and profit functions are quasi-concave, then both smartphone firms would choose exclusivity. The model described above meets their criteria.

2. There exist values of K such that a rational Firm A would choose not to enter in the absence of exclusive contracts. Furthermore, if the incumbent is exclusive, the entry incentive is even greater when exclusive contracts are available. This is a direct result of the above, but is interesting in that it provides evidence that exclusive contracts increase the returns to innovation.

What is driving this result? A major force at work is that downstream Bertrand competition drives markups to zero, and so exclusivity provides a buffer against price competition. The exclusive contract alters the response curves of the upstream firms, taking advantage of the fact that prices are strategic complements. Below I will extend the general model to the case of differentiated goods at both upstream and downstream levels and show that under certain conditions, exclusivity is the optimal contract. In many realistic settings, downstream firms are differentiated or contributed a differentiated good to the end product, and so this generalization is relevant.[20]

2.2 General Model

We can think of the case above as a limit case where downstream firms are perfect substitutes to consumers. Another limit case is where downstream firms are not substitutes at all, or where wireless carriers are effectively monopolists over their customers. In that setting, it is clear that exclusivity can not be optimal for an upstream firm, as they could do strictly better selling to 2 or more downstream firms, as each carrier is effectively a separate market. Figure 2 illustrates the profits to the entering upstream firm at different levels of downstream market power, and for different contracts, providing a roadmap to this section. I maintain throughout the assumption that competing handsets are imperfect substitutes and that prices of handsets are strategic complements. For simplicity, I will assume that the underlying demand system captures downstream "substitutability" with a parameter $\eta \in [0,\infty)$, such that under common agency, when $\eta = 0$, downstream firms are perfect substitutes as in the above section so that for carrier n , where s_{An} is the share of handset A on carrier n, we have that $\frac{\partial s_{An}}{\partial p_{An}} = -\infty$. As η increases, so does $\frac{\partial s_{An}}{\partial p_{An}}$, and in the limit $\frac{\partial s_{An}}{\partial p_{An}} \to \frac{\partial s_A}{\partial p_A}$ as $\eta \to \infty$. This allows us to characterize the limit cases of carrier monopolists

[20] Whinston (2006) states with regard to multibuyer/multiseller settings that "developing models that reflect this reality is a high priority."

($\eta = \infty$), carriers as perfect substitutes ($\eta = 0$), and cases in-between. As an example of how such a parameterization could arise, consider a standard Hotelling setup where the transport cost across the unit interval is given by η: when $\eta = 0$, all consumers are equally willing to go to either end of the interval, and as η increases, consumers are less willing to substitute to the firm that is located further from them. Appendix D details additional examples of demand systems with this property.

We will now consider the general case of two upstream firms as before, but now N downstream firms that are imperfect substitutes. Under non-exclusivity for both A and B, the maximum possible profits for firm A under a two-part tariff are given by the profits earned from selling directly to consumers:

$$\pi_A^{C*} = \frac{s_A\left(p_A^{C*}, p_B^{C*}\right)^2}{-\frac{\partial s_A}{\partial p_A}}$$

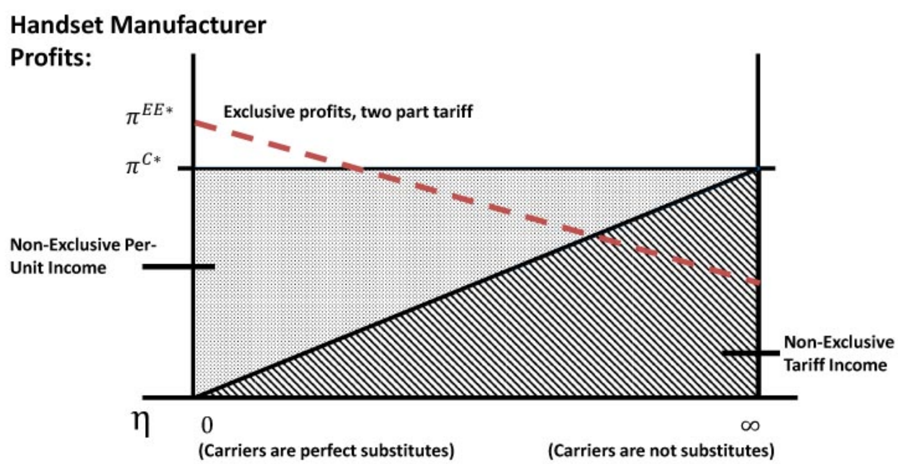
The details of how this is achieved at any η are in Appendix D.

Under exclusivity, carriers 1 and 2 have exclusivity of products A and B respectively, and choose markups based on the wholesale prices they are charged. It is easy to show that these markups are greater than the markups they choose under common agency at a given wholesale price. Knowing the expected markup functions, the handset makers choose wholesale prices to maximize their joint profits with their exclusive carrier. This yields a best response function for each of the handset makers that is far steeper than the common-agency setting. Let $m_h(q_A, q_B)$ denote the carrier's markup function for handset h, and note that it is decreasing in own wholesale price but increasing in opposite wholesale price. We have a best response function for Firm A of

$$q_A - c = -m_A + \frac{\left(1 + \frac{\partial m_A}{\partial q_A}\right) s_{A1}}{-\left(\frac{\partial s_{A1}}{\partial p_{A1}}\left(1 + \frac{\partial m_A}{\partial q_A}\right) + \frac{\partial s_{A1}}{\partial p_{B2}}\frac{\partial m_B}{\partial q_A}\right)}$$

We see that the handset maker effectively replaces the carrier's markup with a more optimal one, which is based on a lower elasticity when prices are strategic complements (as captured by $\frac{\partial s_{A1}}{\partial p_{B2}}\frac{\partial m_B}{\partial q_B}$). This results in a higher retail price for both handsets, and profits under exclusivity of π_A^{EE*}. Figure 2 summarizes the upstream profits under different contract forms at different levels of downstream market power.

Figure 2: Upstream Firm Profits by Contract and Downstream Market Power



We can now turn to our first result:

Proposition 1. *In the above model, if (a) prices are strategic complements, (b) shares are smooth and twice continuously differentiable in prices, (c) the price equilibrium exists, is unique, and continuous, then there exists a value* η^* *such that for all* $\eta < \eta^*$*, exclusivity is jointly profit maximizing.*

The proof follows from the fact that final retail prices are higher under exclusivity, but market share is lower (except in the case of carriers as perfect substitutes). The formal proof relies on continuity and the Intermediate Value Theorem, since $\pi_A^{EE*}(\eta = 0) > \pi_A^{C*}$, but $\pi_A^{EE*}(\eta = \infty) < \pi_A^{C*}$. From the proof, we can see that the range of downstream elasticity over which exclusivity is optimal is (a) decreasing with N, the number of wireless carriers, (b) increasing with the degree of complementarity of prices, and (c) decreasing with the elasticity of upstream demand. These are all intuitive findings: the first captures the fact that as the number of downstream firms increases, so does the opportunity cost of exclusivity. The second captures the degree of the pricing advantage of exclusive contracting, and the third captures the influence exclusivity will have on downstream market shares.

Lemma. *The existence of exclusive contracts can lead to entry in cases where it would not be profitable otherwise.*

This lemma is a direct consequence of the above proposition. There is a non-empty range of entry costs such that entry is not profitable in the absence of exclusive contracts, but is profitable with exclusivity.

Until now we have considered downstream firms to be identical and horizontally differentiated. Suppose now that for simplicity there are only two downstream firms (carriers) and that they also differ in a vertical characteristic. One example of this for wireless carriers could be the quality of their network (e.g. dropped call rate). Suppose further that a handset maker has decided to enter exclusively. When might we expect one carrier or the other to be the most profitable match for exclusivity? Assume that a carrier would be willing to pay up to its profit difference between exclusivity and rival exclusivity (i.e. AT&T would have been willing to pay Apple up to its profit difference between AT&T-Apple exclusivity and Verizon-Apple exclusivity).

Based on the model above, it seems intuitive that a carrier that faces more elastic demand would have the most to lose from a rival gaining exclusivity, as it would face a larger change in equilibrium price. Assume that consumers observe a vertical characteristic of each carrier n, δ_n, with $\delta_n \neq \delta_{n'}$ and price elasticity at a given price decreasing in δ_n. Further assume that consumer utility for the handset-network bundle (δ_A, δ_n) takes the form $u_{An} = \delta_A + \delta_n + \beta\delta_A\delta_n - p_{An}$. This form is chosen as the interaction term allows consumers to "substitute" between handset and network quality $(\beta < 0)$, or it allows a better network to make a handset even better $(\beta > 0)$.

Proposition 2. *For the case of two otherwise identical carriers with $\delta_1 < \delta_2$, there exists a β^* such that the carrier 1 is willing to pay more for exclusivity for all $\beta < \beta^*$.*

If consumers are willing to trade-off handset and network quality, then the handset is worth relatively more to the lower quality carrier. Once β gets high enough, its value is sufficiently augmented by the higher quality carrier for it to be willing to pay more. This tells us that measuring whether or not consumers are willing to substitute between handset and network quality will be a determinant of a carrier's willingness to pay.

This section has established that exclusive contracts can be jointly profit maximizing depending on the relative elasticities of the two markets. The primary mechanism is through an increase in effective elasticity when setting prices, although these contracts can also encourage new entrants. When carriers are also vertically differentiated, we see that consumers' willingness to substitute between handset and network quality will affect which downstream firm values exclusivity more.

3 Industry and Data Description

3.1 The United States Wireless Market

There are four nationwide wireless carriers in the United States who together control approximately 85% of the market: Verizon, AT&T, Sprint, and T-Mobile. Smaller, regional carriers account for the balance. Mobile phone penetration is high, with 95% of adults owning mobile telephones by the end of 2010. Smartphones are a fast-growing segment of mobile telephones: despite the first smartphones appearing in the 1990s, smartphones never achieved widespread consumer adoption until advances in cellular data networks and increases in the power of mobile devices led smartphones to dominate new mobile telephone purchases in 2011.[21] Smartphones differ from traditional mobile phones ("feature phones") in that they offer rich data services such as e-mail, web browsing, photo and video capture, and multiple software applications in addition to voice features. The dominant smartphone operating systems are Apple's iOS, Google's Android, and Research in Motion's Blackberry. Of those three, Android is the only one whose owner does not control hardware as well: Google has several hardware partners that build and market smartphones, including Motorola, Samsung and HTC.

Wireless carriers purchase spectrum from the US government and construct and operate wireless networks, offering consumers various monthly packages of voice and data usage. Smartphones are typically sold on subsidized two year contracts: consumers commit to two years of a monthly plan that includes a data component in exchange for being able to purchase a smartphone at a reduced price. The subsidized price of a smartphone typically falls between \$0 and \$250, whereas the unsubsidized retail price is often between \$500-\$700. Monthly plans for smartphones range from \$65 to \$130, depending on the features that are included.

The fact that smartphones are sold on two-year contracts introduces the fact that the choice to buy a new handset is a dynamic one. Purchasing a handset-network bundle in the current month creates a switching cost for the next 24 months due to the early termination fee (ETF) clause common in all contracts. These fees start between \$175 and \$350, and decrease by \$0-10 per month over the length of the contract.[22] Smartphones are subsidized by wireless carriers, so this fee prevents consumers from leaving before the subsidy has been recovered by the carrier.

3.2 Demand data

I use proprietary datasets gathered by The Nielsen Company in my estimation: Nielsen conducts a monthly survey of the United States wireless telecommunications market. Between 20,000 and 25,000 individuals are contacted every month (though, not the same individuals every month) and are asked a series of individual questions including income range, age, race, gender, household size, employment, and education level. They are also asked whether or not they subscribe to mobile phone service, and if so, on which carrier and using which handset with which price plan. The geographic market of the individual is also observed, as is the time since they acquired their current handset, and whether or not they have switched carriers in the previous 12 months.[23] I have

[21] See Nielsen Press Release "In US, Smartphones Now Majority of New Cellphone Purchases," June 30, 2011.

[22] Over the time period in question, T-Mobile's ETF is \$200 for the entire contract length. Verizon and AT&T are both \$175 decreasing by \$5 per month at the beginning of the data period but switch to \$350 less \$10 per month in November 2009 (Verizon) and \$325 less \$10 per month (AT&T) in June 2010. Sprint starts at \$200 and falls by \$10 per month until it reaches \$50, where it remains until the end of the contract.

[23] Unfortunately, I do not observe the previous handset-network bundle, or even the identity of the previous carrier for these individuals.

access to the survey months of November 2008 until December 2010. I omit people under 18 years of age and people who identify that their employer provided their phone to them.[24] The survey observations are assigned weights to correspond to census data. Appendix Table 10 provides some summary statistics.

3.3 Product data

The demand dataset contains the name of the chosen handset and carrier as well as basic data on product characteristics: flags for keyboard, touch screen, smartphone, and brand. I have augmented the dataset with additional characteristics for smartphones including software operating system, processor speed, and the number of "apps" available.[25] Self-reported prices are available by device in the demand dataset, but due to the high variance in the price reported for a handset on a given carrier purchased in a given month, I omit self-reported prices for purchases that occurred more than 3 months before the survey and take the mode of reported values for a given month of purchase. Further, as some models have few reported purchases in a given month, I impose that handset prices be weakly decreasing over time.[26] Discussions with industry sources confirm that at the monthly level, prices for a given handset rarely increase. Network prices are publicly available. I choose the network price for each carrier's introductory smartphone bundle, which during this sample consists of 450 "peak" minutes (500 on T-Mobile), unlimited evening and weekend minutes, unlimited in-network calling, unlimited text message, and unlimited data. There are many combinations of features that can result in different prices, but I chose this price as many add-ons and features are the same price across networks, and so this provides a benchmark. There are other minor differences between the plan prices I use, such as different hours for what qualifies as "evening" and different definitions of "in-network calling", however I allow these differences to be absorbed by carrier fixed effects.[27]

I further augment the demand data with carrier network performance data at the market level taken from periodic "Drive Tests", where a team from Nielsen drives around a market with devices that simulate cell phones and record signal strength, dropped calls, and other performance data of all of the available carriers in the market. This data is collected every 4-6 months for approximately 100 markets across the USA. I linearly interpolate in-between months for these metrics and match the markets to the markets identified in the demand data. The 90 markets for which I have both demand and network quality data form the basis of estimation. These 90 markets represent most

[24]Combined, these represent approximately 4% of observations.

[25]The primary source for the added data was the database of handset characteristics maintained by the website www.phonearena.com.

[26]That is, if the median reported prices paid for a handset in months t and t+1 are p_t and p_{t+1}, I impose that the price in month $t+1$ is p_t in the event that $p_{t+1} > p_t$.

[27]For example, Sprint allows free calls to any mobile number, not just other Sprint customers.

of the 100 largest MSAs, covering over 190 million Americans.

I collapse all non-smartphones into a single "feature phone", available on every carrier at the same fixed price with a mean utility to be estimated. I am left with 211 handset-network bundles over the course of 26 months.[28] In terms of individual handsets, I observe 4 models of iPhones, 18 models of Blackberries, and 43 models of Android phones.

3.4 Data Description and Trends

There are two dominant wireless carriers in the United States: AT&T and Verizon, who each control approximately 30% of mobile customers. They are followed by Sprint (16%) and T-Mobile (11%). Network quality data appears to be highly persistent over time within a market, but exhibits significant variation across markets for all of the carriers. Figure 3 shows a non-parametric density plot of the rate of dropped calls across markets for each carrier in a given month, a plot of the dropped call rates within a sample market over time, and a summary of each carrier's network quality ranks. Note that for contractual reasons, there are certain pieces of data that cannot be fully labeled.[29] In the density plot, it is apparent that each of the carriers competes in markets where their network quality is "good" (few dropped calls) and others where it is "bad" (many dropped calls). However, it is also apparent that some some networks are generally "better", with their distributions concentrated to the left, and some are generally "worse", with their distributions more diffuse. The second plot shows that, in a sample market, the relative rankings of the carriers' network quality does not change over the 26 months that I use for estimation. In fact, the rates barely move at all over the 26 months. The third shows that every carrier has markets where they are ranked each of 1st, 2nd, 3rd and 4th out of the four major carriers in terms of network quality. As a comparison, Consumer Reports conducts an annual survey of 50,000 cell phone customers and publishes carrier ratings for approximately 25 metropolitan areas in every January issue.[30] For the years 2008-2011, Verizon is the highest rated carrier in their survey, although there are individual markets where other carriers are rated superior.

A key trend in this time period is the rapid adoption of smartphones. In the first month of my data, 8% of adults own a smartphone, which triples to 24% in the final month. The share of device purchases in a given month that are smartphones increases from 4% to nearly 20% during this period. In the same period, the share of adults that own any phone increases from 89% to 95%. The solid lines in Figure 5 shows this smartphone trend split out by income group. The mix of smartphones that consumers own also undergoes a dramatic swing: iOS (the operating system

[28] I perform additional data-cleaning activities, such as removing observations of T-Mobile iPhones, which were unauthorized "unlocked" models of the original iPhone.

[29] As some summary statistics from Nielsen's research are made public, there will be occasions where firm names are included.

[30] See, for example, Consumers Union of United States (2009).

used on iPhones) and Android see strong growth, while Blackberry's growth lags the growth of smartphones overall. The solid lines in Figure 6 show the share of adults that own a given type of smartphone over time. By the end of 2010, iOS and Android each control nearly 30% of smartphones.

Another interesting trend is the share of customers under contract. Figure 4 shows that the share of customers that are currently on a contract for their mobile phone does not change much over the sample period, even when restricted to only smartphones. Over 90% of smartphone consumers report signing a two-year contract that includes an ETF.

Additional plots of raw data are discussed with the estimation results in Section 5, where plots of actual versus fitted moments of the data are discussed to illustrate how well the model fits the data at the estimated parameter vector.

3.5 Reduced-Form Evidence

To determine whether or not consumers respond to my measure of network quality, I performed a regression of carrier share on dropped calls for a single month of my data, including carrier fixed effects and clustering standard errors at the market level. The results (Appendix B) show an effect of dropped calls significant to the 99% level, and estimate that a 1% increase in a carrier's dropped call rate translates into a decrease of market share of 0.84%. This indicates that consumers do indeed respond to differences in network quality.

From the theory model, we are interested in estimating the substitutability of handsets versus wireless carriers. However, since the data are not a true panel, we cannot directly look at switching rates between different handset-network bundles. We are interested in distinguishing whether the market is composed of, say, consumers who want a Blackberry regardless of which carrier it is on, or consumers who want to be on Verizon regardless of what handset they have. Treating each market as an independent realization of preferences, we can look at the cross-section for evidence of substitution.

Consider the following: if carriers are good substitutes for one another, we would expect to see wide variance in carrier market shares across markets, relative to the variance in smartphone market shares. See Appendix Figure 9 for plots of these shares across markets in the raw data. We can see that there does appear to be more variation in carrier market shares than in smartphone market shares across markets. However, there are obvious confounds to this: we believe that differences in network quality affect a carrier's market share, as discussed above. Similarly, since the iPhone is exclusive to AT&T, we would expect AT&T's strength in a market to affect the different smartphone market shares. Appendix Figure 10 plots the residuals from regressions of market shares on controls. We clearly see that, controlling for relevant confounds, there is little variation in smartphone shares across markets, but large variation in carrier shares across markets, lending support to the idea that carriers are good substitutes for one another, but smartphones are poor substitutes for one another.

4 Empirical Model of Demand for Smartphones

Utility maximizing consumers choose every month to either consume a handset-network bundle, or to have no mobile phone (with discounted present value of utility normalized to 0). A consumer's state in a given month is what device she currently owns, the months remaining on her contract (if any), and any early termination fee (ETF) that would apply if she chose to switch to a new device or carrier. The consumer chooses between alternatives every month based on the discounted utility from each handset-network bundle.

Monthly Flow Utility I begin with monthly flow utility: An individual i in market m receives flow utility from handset h on network n in month t that consists of a handset component, a network component, an interaction between those two, and a monthly access fee:

$$\begin{aligned} u_{imnht} &= (1-\beta_t)^{(t-t_{i0})}\left[\delta_{imnt}+\delta_{iht}+\beta^c\cdot\delta_{imnt}\cdot\delta_{iht}\right]-\alpha_i\cdot p_n \\ \delta_{imnt} &= \beta_{in}\cdot X_{mnt}+\xi_{nm} \\ \delta_{iht} &= \beta_{ih}\cdot X_{ht} \end{aligned} \tag{1}$$

The term $(1-\beta_t)^{(t-t_{i0})}$ captures a deterministic rate of decay of a handset purchased in month t_{i0} over time, with the monthly decay rate β_t to be estimated. The term β^c is analogous to the one from Section 2.2, and allows consumer utility to be non-linear in the utility of the individual bundle components. Utilities from the handset and network, δ_{imnt} and δ_{iht} respectively, are modeled as projections on to the characteristics of the networks and handsets. Consumers have individual-specific tastes over network characteristics, which consist of network n's rate of dropped calls in market m in period t.[31] There is also a fixed network-market effect ξ_{nm} that is constant over time that captures unobserved heterogeneity in carriers across markets. Similar to network quality, handset quality depends on a vector of handset characteristics over which consumers have random and fixed coefficients: random coefficients over indicators for the Android, iOS, and Blackberry handheld operating systems, and fixed coefficients over processor speed, indicators for feature

[31] The dropped call rates used in estimation are relative to the market average. There exist markets where, for geographic reasons, all major carriers have poor quality networks, but I do not observe less adoption of mobile phones in those markets. Instead, the primary driver of differences in overall mobile phone adoption across markets is the income distributions of the markets. Conditional on owning a mobile phone, the relative shares of the carriers is heavily influenced by their relative quality, as discussed in Section 3.5.

phone and smartphone, time trends in feature phone and smartphone, the log of the number of "apps" available on the handset platform, and whether or not a given device is that network's "flagship" device[32] at that time.[33] The network's monthly access fee is p_n. An individual's price sensitivity, α_i, will be modeled as

$$\alpha_i = \mathbf{Z}_i \cdot \beta_\alpha + \eta_i^\alpha \tag{2}$$

where $\mathbf{Z}_i$ are indicators for an individual's income group,[34] β_α are fixed coefficients and η_i^α is an i.i.d. mean-zero normal draw with variance σ_η to be estimated. The individual-specific random coefficients $\beta_i = [\beta_{in}\,\beta_{ih}]$ multiply the network quality characteristic and a vector of handset operating system dummies, respectively, and are distributed jointly normal according to $\beta_i \sim N\left(\overline{\beta}, \Sigma\right)$. All off-diagonal elements of Σ are set to 0, except those corresponding to covariances between random coefficients of the handset OS dummies and the rate of dropped calls, which are to be estimated. Note that these random coefficients are not subscripted by time period; they are persistent over time.

Discounted Flow Utility A consumer's decision on which device to purchase is clearly a dynamic one: purchasing a device today and signing a two-year contract increases my cost of changing to a new device in the next 24 periods. However, the state space over the 24 months of a smartphone contract consists of all possible characteristics, prices, and availabilities, and so some simplification must be made to make the problem tractable. I assume that at the time of contract signing, a consumer does not expect to break her contract: she evaluates discounted utility without explicitly accounting for the option value of switching in every period between the current one and the end of her contract.[35] In the data, less than 1.4% of observations report paying termination fees in the previous 12 months. Discussions with industry sources indicate that consumers who pay such fees have often either broken their handset, rendering it useless, or are responding to a another truly unexpected event such as a relocation.[36] These are consistent with consumers not

[32]While I observe advertising spending by carrier and market, I do not observe it at the device level. Conversations with industry sources confirm that carriers focus their device advertising on one "flagship" device at a time. Therefore, I have identified each network's "flagship" device for the period in question, and assigned it an indicator equal to that carrier's share of advertising spending in that market and month.

[33]Additional characteristics such as GPS, wifi, memory, screen size, screen resolution, and camera resolution have also been gathered. However, trends in these are highly collinear with processor speed, and so they are not included.

[34]I use 7 income groups in total, as all groups above $100K in income have similar rates of ownership of smartphones in the dataset. Note that the mean income coefficient of the lowest income group is normalized to -1, but for the remaining groups is estimated freely.

[35]When estimating the model, consumers are indeed able to break their contract and switch to a different bundle. Unreported estimates from a model where consumers are not able to switch while under contract yields similar results.

[36]Given the high "retail" (unsubsidized) listed prices of handsets, if a handset is broken, it can often be less expensive to pay an ETF and purchase a new subsidized handset than to replace the previous handset.

expecting to break their contract at the time of signing.[37] A second challenge is how to model the continuation value at the end of a contract. I will borrow a suggestion from other dynamic discrete choice studies[38] and assume that the maximum discounted utility available from a handset-network combination in the current period is sufficient to predict future values of the maximum discounted utility available from a handset-network bundle. This is captured in the continuation value function $\gamma_{it}()$ described below.

Given the flow utility, consumer i in market m that currently owns handset h on network n with r_{it} months remaining on their contract has the following present value of utility from that handset-network combination:

$$U_{imhnt} = \sum_{m'=0}^{r_{it}-1} b^{m'} u_{imnht} + b^{r_{it}} \cdot \gamma_{it}(r_{it}) \tag{3}$$

In every period, a consumer will compare this value to other possible choices available to them. I use the notation $(nh)'$ to indicate an alternative handset-network bundle. A consumer's information set in the current month consists of all characteristics and prices of the products that are available. Specifically, every other handset available on every network, and the outside good of having no mobile telephone. The present value of utility from purchasing a new bundle handset-network pair in period t in market m is

$$U_{im(nh)'t} = \alpha_i \cdot \left(p_{(nh)'t} + ETF_{it} + \beta_i^s\right) + \sum_{m'=0}^{23} b^{m'} u_{im(nh)'t} + b^{24} \cdot \gamma_{it}(24) \tag{4}$$

The discount factor b is fixed at $0.9916 = 0.9^{(1/12)}$, giving an effective annual discount rate of 10%. The term γ_{it} is a reduced-form representation of the consumer's continuation value at the end of their contract. It can be thought of as that person's value of being off contract, and will be modeled as $\gamma_{it}(x) = \theta_\gamma^x \max_{(nh)}\{U_{imnht}\}$. That is, a consumer looks at the discounted utility available from other bundles this month, and expects the maximum of that set to grow by a percentage every month.[39]

The first term in the above equation captures the cost of purchasing the handset at price $p_{(nh)'t}$, paying an early termination fee (ETF) of ETF_{it}, and paying some individual specific intrinsic switching cost β_i^s, designed to capture the cost of learning about new devices, learning how to use a new device, and transferring data. Early termination fees vary by carrier and typically decrease every month from the date of purchase until the contract expires after two years. Consumers who

[37] Unreported estimates of this model omitting observations who claimed to have broken contracts yields similar results to the reported results.

[38] See Gowrisankaran & Rysman (2007) and Geweke & Keane (1996)

[39] The maximum of the set is selected as though the consumer were not currently on a contract, as that is the proper benchmark for modeling the value of being off-contract.

are off-contract in period t have $ETF_{it} = 0$. The 24-month discounting reflects the two-year length of contract.

Therefore, the consumer's decision to consume handset h on network n in a given period is captured by the inequality

$$U_{imnht} \geq U_{im(nh)'t} \ \forall (nh)'$$

4.1 An Alternative Logit Approach

The above model is similar to the Pure Characteristics model described by Berry & Pakes (2007), which omits i.i.d. Logit draws for each possible good and opts instead for only random coefficients to rationalize tastes. If, instead, we were interested in estimating a version of this model with Logit tastes, we could indeed add i.i.d. Logit errors to each discounted flow utility U_{imnht} and directly estimate a likelihood for each survey respondent. However, such a model has several drawbacks, which are discussed in Appendix E.

4.2 Estimation Approach

The approach taken to estimate the above model will be to use a simulation estimator for a small number of markets, but to nest that estimator with a Markov Chain Monte Carlo method to recover estimates for the full dataset.

The simulation estimator I use is the simulated non-linear least squares (SNLLS) estimator proposed by Laffont, Ossard and Vuong (1995). The model described above could also be estimated using a simulated GMM estimator in the spirit of McFadden (1989) or Pakes & Pollard (1989). Given a parameter vector, the model would predict market outcomes for every market and every month given product characteristics and prices. Simulation methods could be used to integrate over the random coefficients, and the simulated moments of the model could then be matched to observed moments of the data. However, as is well-known in this literature, minimizing a naive sum-of-squares of the difference between simulated and observed moments is biased for any fixed number of simulation draws.[40] The SNLLS estimator explicitly corrects for the simulation bias in the objective function, resulting in a consistent estimator that is far less computationally demanding than alternative approaches.[41]

[40] See Appendix F or Laffont, Ossard & Vuong (1995) for details.

[41] An alternative approach to this problem proposed by Gourieroux & Monfort (1993) uses moment conditions of the form

$$E\left[\left(\psi_l^0 - \psi_l^{NS}(\theta)\right)\frac{\partial \psi_l^{NS}(\theta)}{\partial \theta}\right] = 0$$

where different sets of draws are used to compute the simulated moments and their derivatives, respectively, to

A second challenge is that the unobserved heterogeneity parameters, ξ_{nm}, introduce 450 parameters that must be recovered when all 90 markets are included. In practice, no optimization routine would be able to find a global extremum over such a parameter space. The remaining parameters are not independent of the ξ_{nm} terms, complicating estimation of the full set of parameters. My approach is to use a Markov Chain Monte Carlo (MCMC) method proposed by Chernozhukov and Hong (2003) which nests the SNLLS estimator inside an MCMC framework.[42] As they show, for an estimator such as SNLLS, a Markov Chain can be constructed that shares the same distribution as the asymptotic distribution of the estimated parameter vector. Parameter estimates can be taken as the mean of the Markov Chain.

A final challenge is that this type of model faces the "initial conditions problem" (Heckman 1981), where the process that determines a sequence of outcomes must somehow be initialized. For example, when simulating this model, most individuals already own a mobile phone in my first month of data. I cannot take this empirical distribution as given and assume that the random coefficients are distributed independently of the state observed in the first month; a given parameter vector must rationalize that initial state (as discussed in Appendix E). If the conditional distribution is not known, then the ideal approach is to start where there is no initial condition (Pakes 1986). Therefore, I simulate starting 5 years before my data begins, allowing consumers to make decisions once per year in a random month, and then up to 4 times in the final year depending on their random month.[43] The choice set in this initial period is limited to a smaller set of smartphones than truly existed, but that captures the most popular models observed in the first month of data.[44]

For practical reasons, I will first estimate the parameters of the model for a small number of markets using SNLLS, and then use these estimates as the starting point for the MCMC estimation. Estimation using the simulation estimator proceeds as follows:

1. For each of the M markets and $N = 7$ income groups, draw a set of S vectors to represent the unobservable types.

eliminate correlation. Computing the derivative of the simulated moment is computationally costly in this setting.

[42]Nesting a simulation-based estimator within an MCMC approach creates a minor problem: the correction term proposed by Laffont, Ossard & Vuong is consistent for any linear transformation of the objection function. However, the MCMC method involves an exponential transform when calculating jump probabilities to construct the chain. This results in a bias in jump probability for a fixed number of simulations, that goes to zero as the number of simulations goes to infinity. The author is aware of this issue and is currently pursuing multiple approaches to correcting for this issue. Monte Carlo experiments indicate no effect on consistency of estimates. Estimates from Specifications (1) and (2) are not affected by this issue, and comparing estimates from Specification (3) to (2) suggest it does not have a material effect on results.

[43] I chose 5 years because 98.6% of observations in the first month of data claim to have purchased their current smartphone within 5 years; 98.0% is the average for all months.

[44]The prices and release dates for the smartphones available in this "initial period" were gathered by hand. The smartphones included are all iPhones, the Blackberry Curve, Pearl, Bold, 7200 series and 8800 series, the Motorola Q series of Windows phones, the Nokia N75 series, and a "generic" smartphone available on each carrier to capture all others. The generic "feature phone" is also included for each carrier.

2. For each market m, determine a set of weights that, when applied to the N individuals drawn in Step 1, match the observed distributions of the N types in that market. That is, each market is expressed as a mixture of finite types of consumers. Similarly, determine weights for each market that represent their share of the national market.

3. Search over parameter vectors to minimize an objective function (discussed below). For each candidate parameter vector,

   (a) Transform a set of S draws to correspond to the random coefficients $\beta_i \sim N\left(\overline{\beta},\Sigma\right)$ in accordance with the candidate parameter vector.

   (b) For all $N \cdot S$ "drawn individuals" in each of the M markets, simulate the sequence of choices for every month.[45]

   (c) Calculate moments of these sequences that can be matched against observed moments of the dataset.

   (d) Calculate the bias-corrected objective function.

What does a sequence of choices for a "drawn individual" look like? As an example, a sequence of choices may be that an individual in a certain market with a set of taste draws emerges from the initial period and arrives in month 1 of my data with a Blackberry on Sprint and four months remaining on contract. In months 2-7, this individual perceives greater discounted flow utility from her current device, even though her contract expired in month 5 and her handset is decaying at a monthly rate of β_t. However, in month 8, a new iPhone is released and this consumer perceives a higher level of discounted flow utility from the iPhone-AT&T bundle, even after paying for the new handset and paying an internal "switching cost".[46] This consumer buys that bundle and then remains with this bundle through month 26, as no other bundle offered enough of an increase in discounted flow utility in any of months 9-26 to overcome her contract termination fees and internal switching cost. This is a single sequence for a single drawn individual in a single market: I simulate many of such sequences for each market based on different draws of unobservables.[47] Once many sequences have been simulated, they can then be aggregated into moments such as market shares or average characteristics of products (the exact moments used in estimation are discussed in Section 4.3).

[45] The sequences of choices is begun 5 years prior to the start of the dataset, as discussed in Section 4.4.

[46] I estimate the distribution of the switching cost, β_i^s, as a normal truncated at 0 with mean μ_s and standard deviation σ_s. While this captures the implicit cost of learning a new device and transferring data between old and new devices, it may also be capturing frictions such as search costs.

[47] An important feature is that the same draw of unobservables may result in different paths in different markets, due to differences in network quality.

For each moment $l = 1..L$, we want to match the simulated moment $\psi_l^{NS}(\theta)$ to its observed value in the data, ψ_l^0. The bias-corrected objective function subtracts a consistent estimate of the simulation error (discussed in Appendix F), resulting in

$$Q_{LNS}(\theta) = \frac{1}{L}\sum_{l=1}^{L}\left\{\left(\psi_l^0 - \psi_l^{NS}(\theta)\right)^2 - \frac{1}{S(S-1)}\sum_{s=1}^{S}\left(\psi_{sl}^{NS}(\theta) - \psi_l^{NS}(\theta)\right)^2\right\}$$

where $\psi_{sl}^{NS}(\theta)$ is the value of the simulated moment for a single simulation draw and $\psi_l^{NS}(\theta) = \frac{1}{S}\sum_{s=1}^{S}\psi_{sl}^{NS}(\theta)$. Thus, our consistent estimate of the parameter vector is $\theta^* = \arg\min_\theta Q_{LNS}(\theta)$.

Once the above method has recovered an estimate θ^* of the true parameter vector θ^0, the standard inference methods for simulation estimators can be used to recover confidence intervals for all parameter estimates. See Specifications (1) and (2) in the results section for estimates for limited numbers of markets using SNLLS.

The MCMC estimator uses the method developed by Chernozhukov and Hong (2003), which nests an extremum operator within an MCMC framework. The approach is to construct a quasi-posterior density over the parameter of interest according to

$$p(\theta) = \frac{e^{-Q_{LNS}(\theta)}\pi(\theta)}{\int_\Theta e^{-Q_{LNS}(\theta)}\pi(\theta)\,d\theta}$$

where Θ is a compact convex subset of $\mathbb{R}^k$ that contains θ^0, $\pi(\theta)$ is a prior probability distribution, and Q_{LNS} is the objective function from the SNLLS estimator described above. Inspection of this density reveals that it places most weight in areas of the parameter space where $Q_{LNS}(\theta)$ is small, or where the simulated model closely matches the observed data. In order to compute an estimate of θ^0, we can construct a Markov chain whose marginal density is given by $p(\theta)$ and recover our estimates as the mean of the chain. To construct the Markov Chain, I will use the Metropolis-Hastings algorithm with quasi-posteriors suggested by Chernozhukov and Hong (2003), where from a starting value $\theta^{(0)}$, I generate a new candidate vector θ' from a conditional density $q(\theta'|\theta)$, and I update according to

$$\theta^{(j+1)} = \begin{cases} \theta' & w.p.\, \rho\left(\theta^{(j)}, \theta'\right) \\ \theta^{(j)} & w.p.\, \left(1 - \rho\left(\theta^{(j)}, \theta'\right)\right) \end{cases}$$

where the transition probability is given by

$$\rho\left(\theta^{(j)}, \theta'\right) = \min\left(\frac{e^{-Q_{LNS}(\theta')}\pi(\theta')\,q\left(\theta^{(j)}|\theta'\right)}{e^{-Q_{LNS}\left(\theta^{(j)}\right)}\pi\left(\theta^{(j)}\right)q\left(\theta'|\theta^{(j)}\right)}, 1\right)$$

I use a standard normal for $q(\theta'|\theta)$, making the chain a random walk. That is, each candidate vector is centered at the current vector. Further, I specify a flat prior for all terms.[48] This simplifies the transition probabilities for my specification to:

$$\rho\left(\theta^{(j)},\theta'\right)=\min\left(\frac{e^{-Q_{LNS}(\theta')}}{e^{-Q_{LNS}\left(\theta^{(j)}\right)}},1\right)$$

Therefore, if a candidate vector improves the objective function, the chain moves to that point with probability 1. If a candidate vector worsens the objective function, the chain moves to that point with some positive probability that depends on the change in the objective function. Because of this, the chain spends relatively more time in the parameter space where the simulated model fits the observed data. Once the chain reaches a sufficient length, its mean $\bar{\theta}$ can be used to provide a consistent estimate of θ^0.

In summary, consumers have individual-specific taste draws for each carrier, for each of the three handset operating systems, for price sensitivity (as a function of income), for network quality, and for switching costs. These individual tastes are persistent over time. I simulate a large number of sequences of consumer decisions and match moments of the simulated model to moments of the raw data, correcting for bias introduced by simulation error. The total number of parameters to estimate is 34, plus the 5 carrier-market fixed effects per market, for a total of 485 parameters when using all data.

4.3 Identification and Moments

Given that this is a non-linear model, there is not a one-to-one mapping between moments and the parameters that they identify. Nonetheless, it is useful to consider what sources of variation in the data are likely to be influencing different parameters. Network monthly access prices do not change over this period, and so identification of preferences for networks comes primarily from cross-sectional variation in the quality and market share of each network, controlling for each market's income distribution. Prices and characteristics of handsets are changing significantly over time but are the same across markets, and so the time-series variation in these are identifying preferences for handsets, as well as parameters relating to switching costs and the handset decay rate. The variation in ownership rates of feature phones and smartphones between income groups identifies differences in price sensitivities between income groups.

A common concern when estimating tastes for a bundle of two goods (a handset and a network in this case) is confounding correlation of tastes with complementarity between the elements of

[48] The correlation parameters are constrained to be within the interval $[-0.9,0.9]$. The handset decay rate is constrained to be non-negative.

the bundle.[49] In this setting, these separate elements are identified by the cross-section variance in network quality. If, for example, tastes for Blackberries and network quality are correlated, I would expect to see the share of consumers with Blackberries roughly similar across markets, but that consumers sort into the higher quality carriers in each market. If instead, the two elements of the bundle are complements, then I would expect a carrier's share of consumers with smartphones to increase across markets as its network quality increases.

The moments used in estimation are the following for each of the 26 months of data: The first set of moments are market-level shares of each carrier for all phones, and for smartphones only. These influence parameters of tastes for network quality, as well as the variance of network tastes and the market-carrier fixed effects. The second set of moments are national-level shares of each smartphone operating system and average characteristics by smartphone operating system (including network quality). These moments drive the taste parameters for the handset operating systems and characteristics, as well as the correlation parameters between handset types and network quality. The third set is the rate of smartphones purchase. This informs structural parameters such as switching costs and the rate of handset decay. The fourth set of moments are the share of ownership of smartphones, and any phone, by income group. These help isolate price coefficients as well as mean utilities and time trends. The total number of moments being estimated is 24,076 when all 90 markets are included in estimation. When estimating for a single market, the number of moments is 936.

4.4 Other details

Estimation of the SNLLS parameters was done using a simulated annealing algorithm in Matlab, using "mex" files to simulate consumer choices and calculate moments and the objective function. I use Halton Sequence draws to improve coverage and reduce spurious correlation. The distribution of random coefficients for dropped calls and for switching costs are truncated at 0, so that no one may get positive utility from dropping calls or switching devices. The MCMC chain constructed has a total length of 100,000 after a burn-in of 10,000 draws. I group the parameters for the Metropolis-Hastings algorithm into the following groups: (1) price coefficients, (2) characteristics, (3) the ξ_{nm}, and (4) all remaining parameters. The variance of the draws for each parameter group is adjusted after every 100 draws per group to maintain an acceptance rate as close as possible to 0.5.

[49] See Gentzkow (2007) for an analysis of this issue in the context of online newspapers versus print newspapers.

5 Estimation Results and Discussion

See Figures starting at 5 for plots of fitted moments (dashed lines) versus actual moments (solid lines). Parameter estimates start in Table 2 for four different specifications: the first specification is estimated using SNLLS on a single market with 2,800 effective draws from the unobserved parameter vector. The second is estimated using SNLLS on 6 markets using 4,200 effective draws. The third uses the identical setup as Specification 2 but switches the estimation approach to MCMC, to show that the SNLLS and MCMC approaches produce similar results. The fourth is estimated using MCMC on 90 markets with 18,900 effective draws. Figure 8 gives examples of the MCMC process. The first panel shows the acceptance rate for the first parameter group. The second panel shows the movements of a single parameter, the price coefficient mean for group with income of \$100K+. The vertical black bars indicate the transition between the burn-in period and the period used in calculating estimates. As can be seen, the process appears to settle into a stationary distribution before the end of the burn-in period.

5.1 Discussion

There are a number of trends to highlight in the parameter estimates. First, many parameters are estimated more sharply as the number of draws and number of markets used increase. A large number of parameters are not significant when using only a single market (Specification 1). This is to be expected, as characteristics such as the network quality vary across markets much more than they do over time. Therefore, we would expect parameters such as the distribution of tastes for network quality and the correlation parameters to be poorly estimated with few markets. Second, the MCMC method provides similar results to the SNLLS for the overlapping specifications. This comparison provides a consistency check that the MCMC method provides an equivalent approach to the SNLLS method. The parameters that are least similar between the two are parameters such as the correlations, which are poorly estimated in general with a small number of markets. Third, note that the 6 markets used for Specifications 2 and 3 are the six largest markets in the sample. These appear to be a selected group, as some parameters show large swings when moving to the 90 markets, particularly those that are identified by cross-market variation.

Looking at the parameter estimates themselves, we see that the price coefficients are sharply estimated and are decreasing in magnitude as income increases. All characteristic coefficients have the expected sign. Other parameters of interest show that there is weak evidence of consumers substituting between handset and network quality, and that the most significant correlation between handset and network tastes is with the Blackberry, where consumers who have positive taste for Blackberries also have stronger disutility from dropped calls. The estimated distribution of switching costs has a mean of approximately \$80, but a large standard deviation. Handsets decay at a rate of approximately 1% per month.

The plots of fitted moments versus actuals based on Specification 4 show that at the estimated parameter vector, the simulated model fits most of the data well (starting at Figure 5).

6 Counterfactuals

6.1 Willingness to Pay for Exclusivity

This counterfactual examines, ex-ante, which of the national wireless carriers had the most to gain from an exclusive contract with Apple in 2007. Of most interest are the values for AT&T and Verizon, as these are the carriers that were rumored at the time to be in discussions with Apple. Prices for the iPhone device are fixed at their values from AT&T regardless of the carrier, but monthly access prices are allowed to re-adjust where indicated in Table 8. The scenarios determine the net change in monthly fee income from November 2008 until December 2010 for all carriers when the exclusive carrier is Sprint, Verizon, and AT&T. The willingness to pay is defined as the total profit with exclusivity less the profits from AT&T having exclusivity (for AT&T, it is compared to Verizon having exclusivity).[50]

If prices are held fixed (first column of Table 8), we see that Verizon has the highest willingness to pay, as they are able to attract a large number of subscribers when offering the iPhone. However, the theory motivation presented earlier indicated that the primary driver of exclusivity being optimal is the change in price equilibrium. In order to determine a new price equilibrium, I numerically estimate the price elasticity of demand for each carrier at the estimated parameter vector, and use this to recover an estimate of each carrier's marginal cost. Then, taking that marginal cost as given, I re-assign the iPhone devices to other carriers, and starting at the observed prices, iterate best responses for each carrier until a new equilibrium is found.[51] I then determine the change in profits at the new equilibrium.

Once prices are allowed to adjust (second column of Table 8), we see that AT&T has a significantly higher willingness to pay. This is due to the fact that AT&T's equilibrium price without exclusivity is lower than Verizon's. Verizon enjoys less elastic demand, and so has less harm from rival exclusivity than AT&T.

The final two columns change the estimate of β^c, the degree to which consumers are willing to trade-off between handset and network quality, to 0. The purpose of this is to determine how much this substitution is affecting willingness to pay. Since setting this parameter to 0 effectively increases utility from all handsets, we cannot compare the values to those of the first two columns.

[50] Verizon is considered to include Alltel, even though that merger was announced in June of 2008.

[51] I cannot prove that there is a unique equilibrium.

However, we still observe the large reversal in willingness to pay once prices float. This is evidence that consumers' substituting handset and network quality is far less of a factor in determining willingness to pay than the shift in price equilibrium.

6.2 Effect of Apple Exclusivity on Android Entry Incentives

This counterfactual considers the expected profits of the Open Handset Alliance[52] had Apple instead chosen to be available on more than one carrier. The scenario compares the variable profits from handsets earned from sales of Android units between November 2008 and December 2010 under the assumptions that the iPhone had initially launched on AT&T and Verizon, or on all four national carriers. All characteristics are held constant at their observed values.[53] Estimates are reported for the case where network prices are held constant at their observed values, and also when they are allowed to float to new optimal prices. Marginal contribution per handset is assumed to be $139, and is the average handset subsidy paid by the three largest wireless carriers in Q4 2010.

As can be seen in Table 9, the exclusivity between Apple and AT&T created a significant opportunity for the Android handset manufacturers. Consistent with the theory model, had Apple not chosen to be exclusive, expected profits for Android handset makers would have been lower by approximately $850M if the iPhone had also launched on Verizon, and nearly $1B if the iPhone had launched on all carriers. In the interest of comparing magnitudes, the 2010 net profit of HTC, one of the most successful Android handset makers, was $1.3B.[54] Therefore, this is a sizable change in incentives.[55] We can conclude that the existence of exclusive contracts creates a significant incentive for entry in this setting.

6.3 Apple Exclusivity vs Non-Exclusivity

This counterfactual combines the results from the previous two to answer the question of how much Apple could have been compensated for the sales it lost due to exclusivity. Looking at AT&T's willingness to pay calculated above, the amount that AT&T would have willing to pay Apple for every iPhone that they *could have sold*, had they not been exclusive, is $148.33. This is based on AT&T's willingness to pay as computed in Counterfactual 1, and the number of handsets

[52] The "Android Consortium", a consortium of 84 companies that includes 22 handset manufacturers, among them Motorola, Samsung, and HTC.

[53] The most obvious characteristic that may change would be the number of "apps" available on Android, as we might expect this to be a function of the installed base of Android phones. This leads to a more conservative estimate of the number of lost sales. Future work will examine this more closely.

[54] HTC Corporation 2010 Annual Report.

[55] Furthermore, it is a conservative estimate. In addition to the issue mentioned in the previous footnote, this does not take into account changes in subsidies or handset prices. It is not feasible to recompute a new handset price equilibrium given the number of prices this would involve (every handset, every month).

Apple could have sold under non-exclusivity in Counterfactual 2. As a comparison, Apple's 2010 net income for the entire firm was $14B, and the firm sold 40M iPhones worldwide.[56] If half of the current year's profits are from current iPhone unit sales, we get $175 profit per unit, which is comparable to what AT&T would have willing to compensate Apple for unit sales foregone due to exclusivity. Without more details on Apple's per-unit profit level, it is not possible to conclusively state that exclusivity was optimal, but this calculation shows that AT&T's willingness to pay was comparable to what Apple is likely able to earn per iPhone sold.[57]

7 Conclusions

This paper proposes a simple motivation for exclusive contracting in the smartphone market: since consumers are more willing to substitute between downstream goods (wireless networks), an exclusive contract with an upstream firm (handset maker) can reduce price competition and lead to higher equilibrium prices. However, since the downstream goods are not in fact *perfect* substitutes, exclusivity leads to a smaller market potential, and so the question of whether or not it leads to higher joint profits of the contracting parties is an empirical question.

An econometric analysis of this market shows that consumers are far more price sensitive with respect to wireless networks than handsets, and so exclusivity may be a profit-maximizing strategy. Counterfactual simulations show that AT&T was indeed willing to sufficiently compensate Apple for the smaller market potential caused by exclusivity, and that this exclusive contract significantly increased the entry incentives of rival smartphones, such as those running Google's Android operating system.

Future research directions include extending the theory model to examine the optimal length of exclusivity under some alternative assumptions, such as decreasing marginal costs or positive usage externalities. These may explain why we observe shorter length exclusive contracts and why Apple renegotiated its exclusivity with AT&T before the end of the 5-year term.

[56] Apple Corporation 2010 Annual Report

[57] Some may argue that the relevant comparison is with the case where Google's Android does not enter, as Apple may not have anticipated Android's 2008 entry into the market. However, Google had purchased the software developer responsible for Android in 2005, and so it is reasonable to assume that Apple anticipated such an entry.

References

[1] Aghion, Philippe, and Patrick Bolton. 1987 . "Contracts as a Barrier to Entry." A.E.R. 77: 388-401.

[2] Asker, John. 2005. “Diagnosing Foreclosure due to Exclusive Dealing,” Leonard N. Stern School of Business, NYU mimeo.

[3] Bernheim, B. Douglas and Michael D. Whinston. 1998. “Exclusive Dealing.” The Journal of Political Economy, Vol. 106, No. 1, pp. 64-103

[4] Berry, Steven and Ariel Pakes. 2007. “The Pure Characteristics Demand Model," International Economics Review, v. 48(4), Special Issue Economics to Econometrics: Contributions in Honor of Daniel L. McFadden, Charles F. Manski and Whitney Newey, eds., pp. 1193-1225.

[5] Bork, Robert H. 1978. “The Antitrust Paradox: A Policy at War with Itself.” New York: Basic Books.

[6] Chernozhukov, Victor, and Han Hong. 2003. “An MCMC approach to classical estimation.” Journal of Econometrics 115, pp293 – 346

[7] Consumers Union of United States, 2009. “CELL PHONES: Our tests of 70 standard and smart models show they’re sharing many more features,” Consumer Reports, vol. 74 no. 1 pp. 34. Albany, NY.

[8] Gentzkow, Matthew. 2007. “Valuing New Goods in a Model with Complementarities: Online Newspapers,” American Economic Review. 97 (3). June 2007.

[9] Geweke, John F. and Michael P. Keane. 1996. “Bayesian Inference for Dynamic Discrete Choice Models Without the Need for Dynamic Programming,” Federal Reserve Bank of Minneapolis Working Paper 564.

[10] Gourieroux, Christian and Alain Monfort. 1993. “Simulation-based inference,” Journal of Econometrics 59, 5-33.

[11] Gowrisankaran, Gautam and Mark Rysman. 2011. “Dynamics of Consumer Demand for New Durable Goods,” mimeo.

[12] Heckman, J. J. 1981. “The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process,” in

Structural Analysis of Discrete Data with Econometric Applications, ed. C. F. Manski and D. McFadden. Cambridge, MA: MIT Press, 179-195.

[13] Katz, Michael L. 1989. “Vertical Contractual Relations,” Handbook of Industrial Organization, Volume I, Chapter 11.

[14] Laffont, Jean-Jacques, Hervé Ossard, and Quang Vuong. 1995. “Econometrics of First-Price Auctions.”, Econometrica, Vol. 63, No. 4, pp. 953-980

[15] Lee, Robin. 2010. “Vertical Integration and Exclusivity in Platform and Two-Sided Markets,” New York University mimeo.

[16] McFadden, D. 1989. "A Method of Simulated Moments for Estimation of Discrete Response Models," Econometrica, 57, 995-1026.

[17] Pakes, A. 1986. “Patents as Options: Some Estimates of the Value of Holding European Patent Stocks," Econometrica, vol. 54, no. 4, pp. 755-784.

[18] Pakes, A., D. Pollard. 1989. “Simulation and the asymptotics of optimization estimators.” Econometrica 57 (5), 1027–1057.

[19] Posner, R.A. 1976. “Antitrust law: An economic perspective.” Chicago: University of Chicago Press.

[20] Rey, Patrick and Joseph Stiglitz. 1995. “The role of exclusive territories in producers’ competition.” RAND Journal of Economics 26(3): 431-451.

[21] Segal, I., Whinston, M.D.. 2000. “Exclusive contracts and protection of investments.” RAND Journal of Economics, Vol. 31, 603–633.

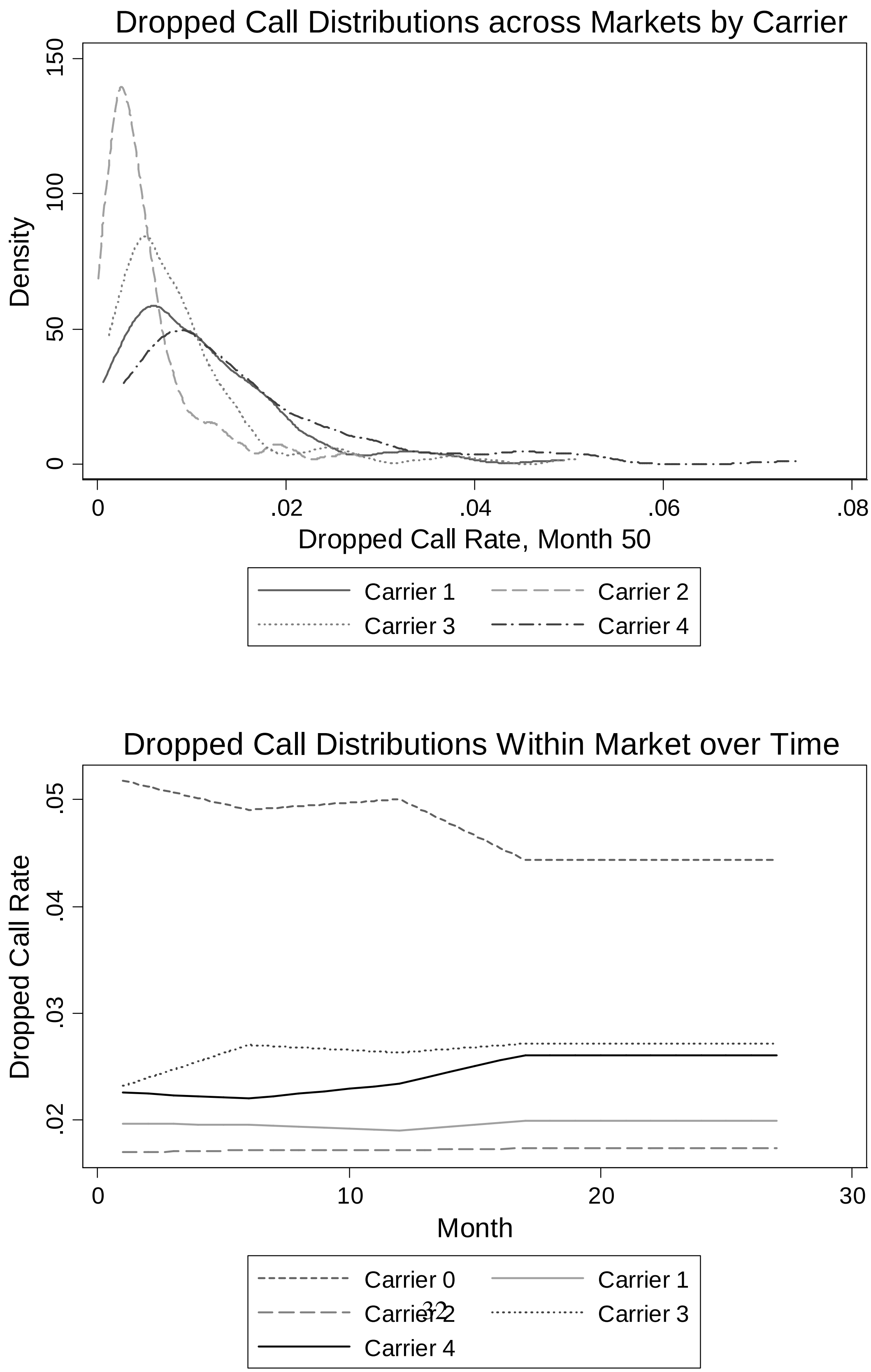
[22] United States Supreme Court. 1977. “433 U.S. 36 CONTINENTAL T. V., INC., ET AL. v. GTE SYLVANIA INC.”

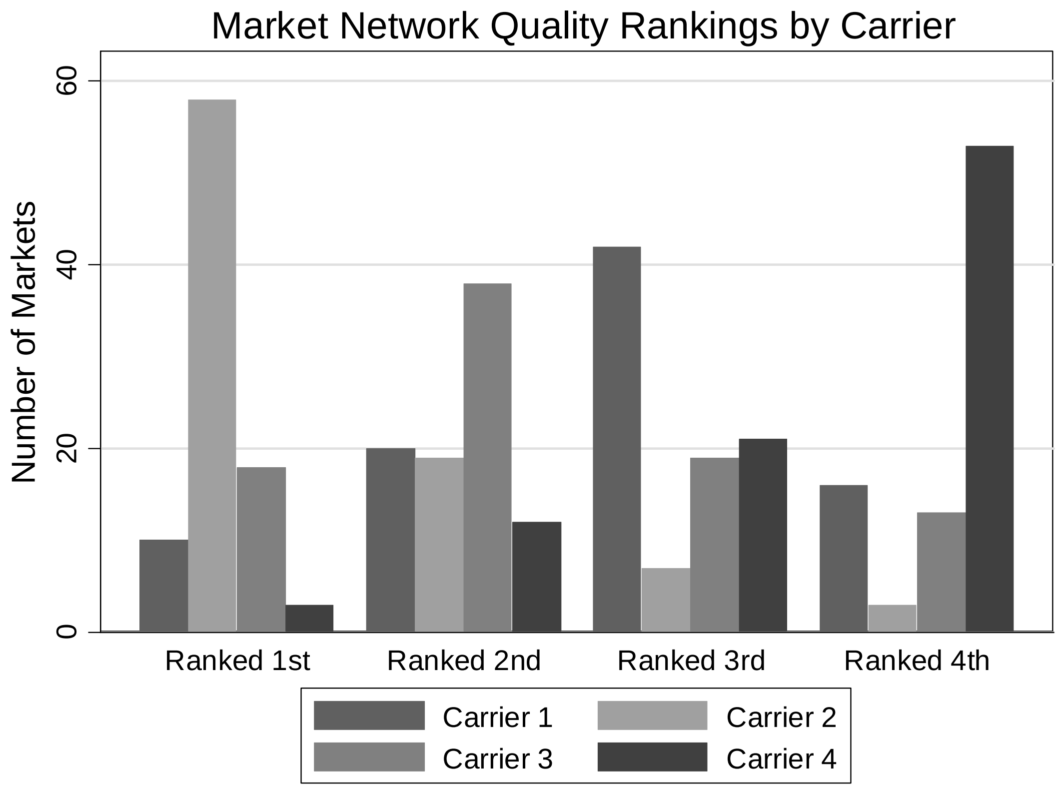
[23] Whinston, Michael D. 2006. “Lectures on Antitrust Economics,” MIT Press.

[24] Zhu, Ting, Hongju Liu and Pradeep K. Chintagunta. 2011. “Wireless Carriers’ Exclusive Handset Arrangements: An Empirical Look at the iPhone,” NET Institute working paper.

Figures

Figure 3: Network Quality Across Markets vs Within Market





Note: “Carrier 0” is all other carriers besides the four national ones. There exist markets where there is no carrier beyond the four major ones, and so I omit “Carrier 0” from the first and third panels.

Figure 4: Share of Consumers on Mobile Phone Contracts

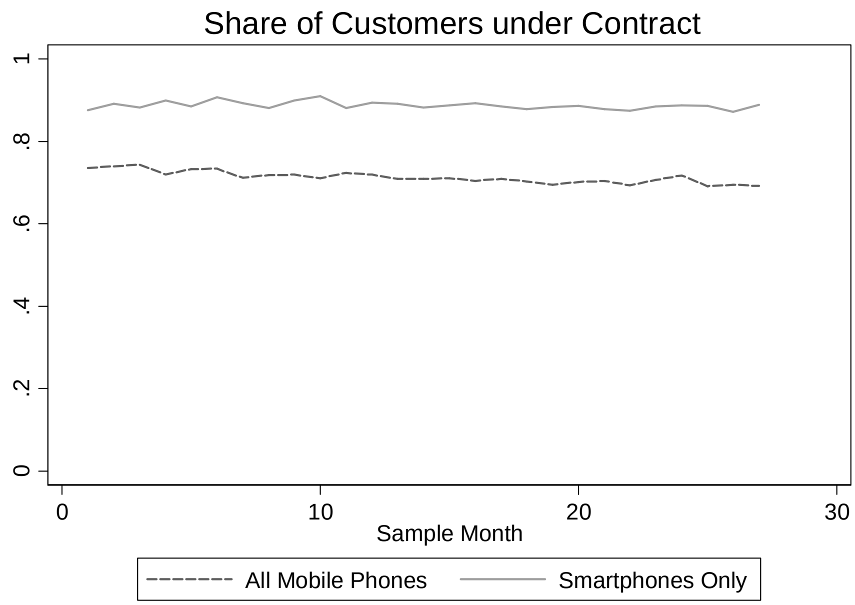
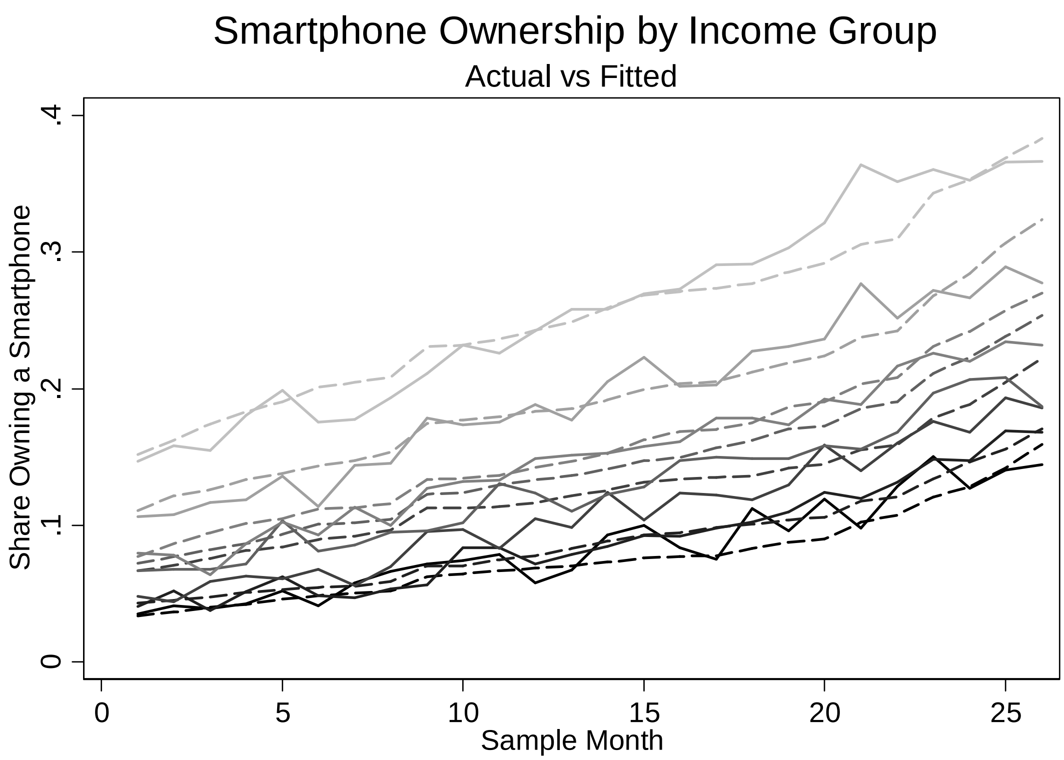
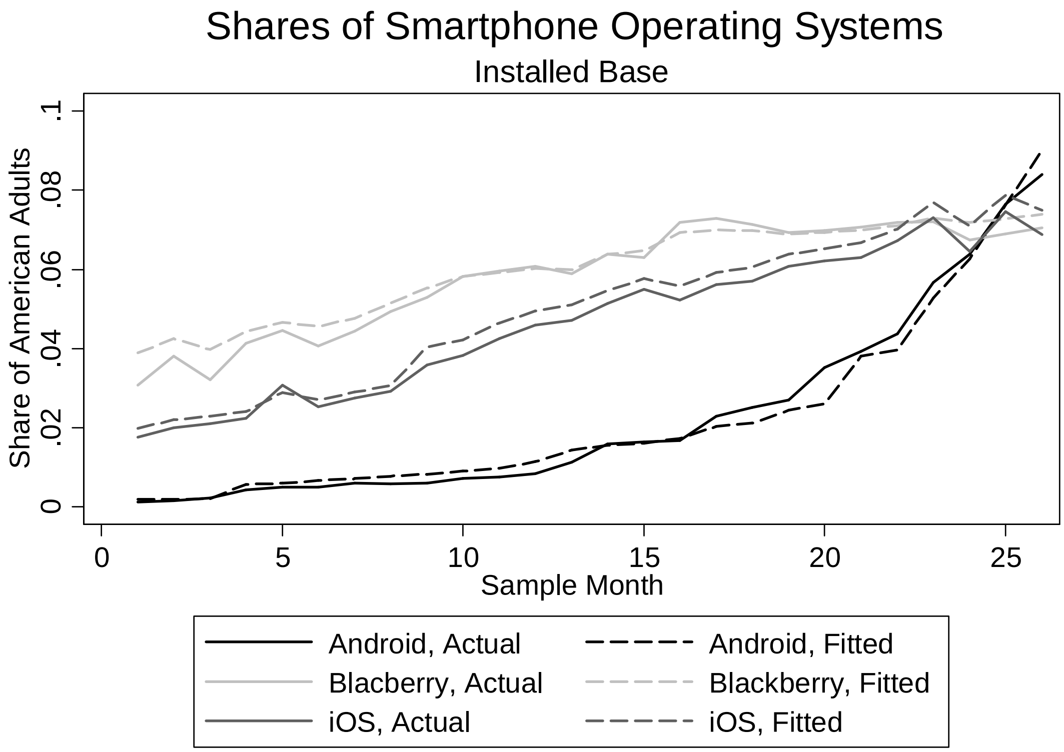


Figure 5: Fitted vs Actual: Smartphone Ownership by Income



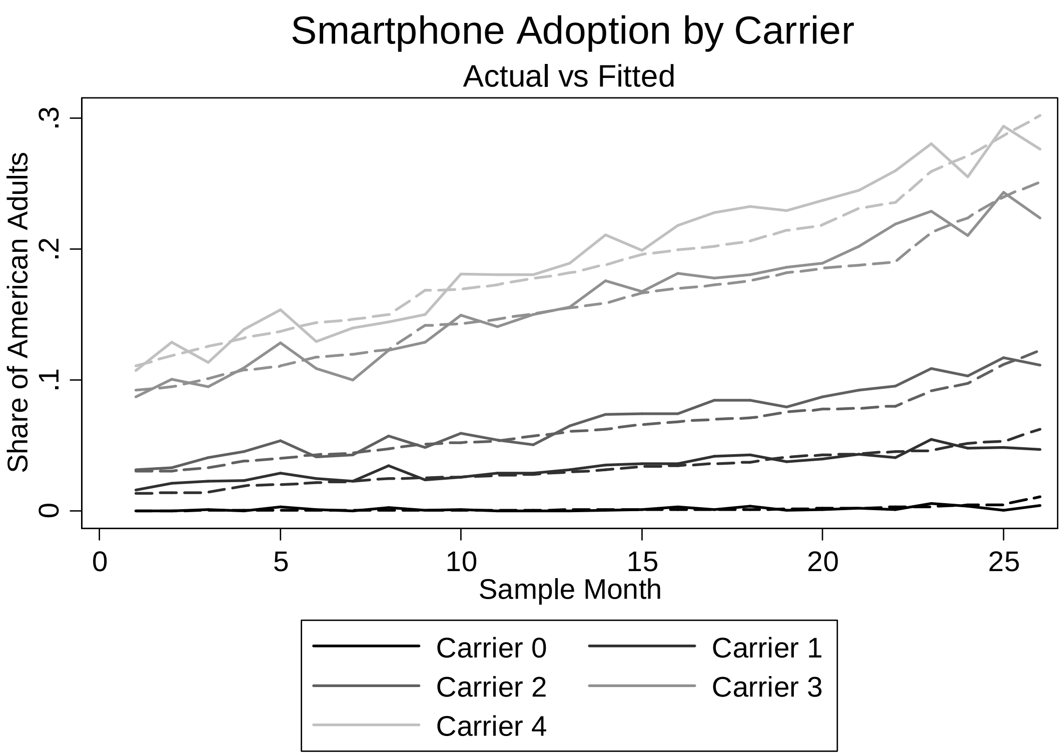
Note: Solid lines represent actual data. Dotted lines are fitted. Different shades represent different income groups; top (lightest) line is incomes of 100K+, decreasing in order to lowest line representing incomes of $15K or less. Ordering reflects ordering in Table 2. Based on results from Specification 4.

Figure 6: Fitted vs Actual: Handset O/S Shares



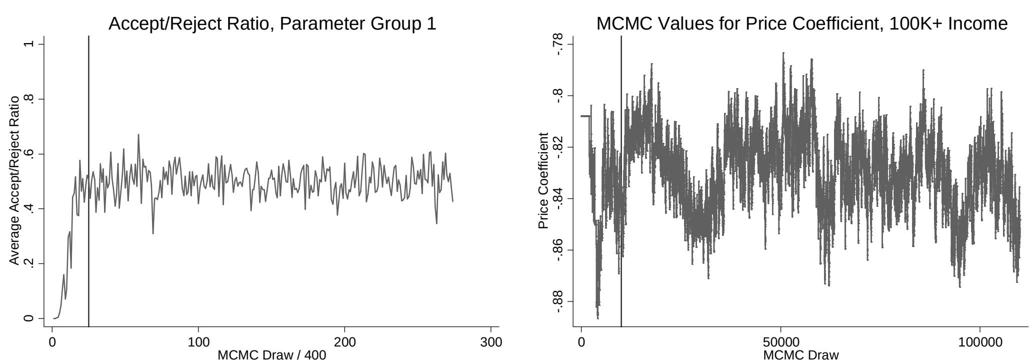
Note: Solid lines represent actual data. Dotted lines are fitted. Based on results from Specification 4.

Figure 7: Fitted vs Actual: Carrier Shares of Smartphones



Note: This graph stacks the share of American adults with a smartphone on a given carrier, showing actual (solid line) versus fitted (dashed line), using estimated from Specification 4.

Figure 8: MCMC Convergence Charts



Note: Vertical bars indicate the end of the “burn in” period. Based on results from Specification 4.

Tables

In all tables, a dash (-) for a standard error indicates that the parameter was fixed in the given specification. Any parameters listed with a μ or σ are indicating that the estimated parameters are means and standard deviations of random normal variables, respectively.

Table 2: Price Coefficient Estimates

	Specification			
Income Group	(1)	(2)	(3)	(4)
<$15K	-1	-1	-1	-1
	-	-	-	-
$15-25K	-0.97614	-0.9759	-0.9871	-0.9758
	(0.0692)	(0.0464)	(0.0406)	(0.0325)
$25-35K	-0.9345	-0.9340	-0.9556	-0.9340
	(0.0993)	(0.0382)	(0.0241)	(0.0118)
$35K-50K	-0.9143	-0.9138	-0.9337	-0.9139
	(0.0416)	(0.0389)	(0.0341)	(0.0252)
$50-75K	-0.8978	-0.8973	-0.8966	-0.8973
	(0.1033)	(0.0489)	(0.0416)	(0.0275)
$75-100K	-0.8579	-0.8578	-0.8589	-0.8578
	(0.2419)	(0.0936)	(0.1223)	(0.0439)
$100K+	-0.80818	-0.8129	-0.8296	-0.8231
	(0.4109)	(0.0217)	(0.0330)	(0.0207)
Standard Deviation	0.1583	0.1578	0.1595	0.1623
	(0.0472)	(0.0319)	(0.0388)	(0.0176)

Table 3: Handset Parameter Estimates

	Specification			
	(1)	(2)	(3)	(4)
Android μ	-9.8975	-9.9737	-9.923	-10.225
	(6.918)	(4.353)	(4.541)	(2.232)
Android σ	7.1402	7.1697	6.8054	7.1763
	(7.164)	(5.291)	(4.541)	(2.366)
iOS μ	-3.9514	-3.9692	-3.842	-3.969
	(8.662)	(7.930)	(6.837)	(2.461)
iOS σ	5.8701	5.887	6.063	5.897
	(2.214)	(5.024)	(4.622)	(1.752)
Blackberry μ	-21.517	-22.162	-22.046	-22.204
	(11.449)	(8.702)	(10.377)	(5.297)
Blackberry σ	18.721	18.647	18.602	18.581
	(13.201)	(5.092)	(3.836)	(3.771)
Log(Apps)	1.9621	1.9792	1.7743	1.9796
	(0.553)	(0.848)	(0.750)	(0.320)
Processor Speed (GHz)	1.1777	1.1857	1.2754	1.1773
	(0.778)	(0.821)	(0.684)	(0.727)
Flagship Device	0.7843	0.7898	0.7113	0.7896
	(0.485)	(0.352)	(0.257)	(0.0674)

Table 4: Network Parameter Estimates

	Specification			
	(1)	(2)	(3)	(4)
Voice Mean Utility	44.793	44.221	44.855	44.551
	(4.457)	(1.972)	(1.378)	(0.570)
Voice Time Trend	5.3892	5.6967	5.8096	5.7028
	(1.964)	(1.591)	(1.735)	(0.671)
Data Time Trend	2.0452	1.9618	1.9479	1.9796
	(0.775)	(0.646)	(0.781)	(0.201)
Dropped Calls μ	-20	-24.024	-24.084	-24.056
	-	(14.265)	(8.163)	(1.310)
Dropped Calls σ	20	17.077	16.896	17.072
	-	(9.002)	(10.816)	(4.524)

Time trends are based on log(month), where month begins at 1 in the "initial period", 5 years before the data begin.

Table 5: Carrier Parameter Estimates

	Specification			
	(1)	(2)	(3)	(4)
Carrier 0 σ	-	0.2314	0.2196	0.2314
("all other" carriers)	-	(0.2613)	(0.2648)	(0.0725)
Carrier 1 σ	0.2969	0.3086	0.2968	0.3015
	(0.2495)	(0.3114)	(0.2967)	(0.0964)
Carrier 2 σ	0.4108	0.4138	0.4319	0.4139
	(0.1613)	(0.2409)	(0.2512)	(0.0941)
Carrier 3 σ	0.5300	0.5376	0.5449	0.5341
	(0.4688)	(0.2062)	(0.2552)	(0.117)
Carrier 4 σ	0.3317	0.3373	0.3708	0.3668
	(0.1328)	(0.3325)	(0.4352)	(0.1964)

Table 6: Correlation Coefficient Estimates

	Specification			
Dropped Call Correlation with	(1)	(2)	(3)	(4)
Android	-	-0.125	-0.129	-0.127
	-	(0.1858)	(0.1602)	(0.0661)
iOS	-	-0.0582	0.0745	-0.0519
	-	(0.1645)	(0.1786)	(0.1412)
Blackberry	-	-0.394	-0.102	-0.2951
	-	(0.2187)	(0.0404)	(0.0812)

Note: Since dropped calls are considered "bad", a *negative* correlation between handset taste and dropped calls indicates that people who prefer that handset also *dislike* dropped calls.

Table 7: Remaining Parameter Estimates

	Specification			
	(1)	(2)	(3)	(4)
Switching Cost μ	73.613	84.273	83.997	84.396
	(22.331)	(24.850)	(18.367)	(7.774)
Switching Cost σ	93.942	97.013	96.616	97.074
	(30.029)	(21.826)	(32.143)	(14.218)
Handset Decay Rate (β_t)	0.00229	0.00232	0.0018	0.007305
	(0.00443)	(0.00571)	(0.00169)	(0.00231)
Continuation Value (θ_γ)	1.0023	1.0035	1.0052	1.0049
	(0.00585)	(0.00581)	(0.00214)	(0.00199)
Handset-Network Complementarity (β^c)	-0.00155	-0.00156	-0.00211	-0.00185
	(0.00079)	(0.00155)	(0.00144)	(0.000861)

Table 8: Counterfactual Simulation 1: Carrier Willingness to Pay

			Scenario	
Carrier	Prices Fixed	Prices Recomputed	Prices Fixed, $\beta^c = 0$	Prices Recomputed, $\beta^c = 0$
AT&T	\$14.12B	\$21.81B	\$19.85B	\$23.90B
Verizon	\$20.54B	\$3.20B	\$32.12B	\$5.43B
Sprint	\$3.02B	\$6.82B	\$5.66B	\$9.86B

Note: Table shows each carrier's maximum willingness to pay for exclusivity with Apple, defined as the profit difference between exclusivity and the worst case of rival exclusivity.

Table 9: Counterfactual Simulation 2: Android Entry Incentives

	Apple enters on:	
	Two Carriers	Four Carriers
Android Entry Incentive	-\$875.2M	-\$961.4M

Note: Table shows projected change in contribution margin for Android handset makers from Apple entering on multiple carriers instead of being exclusive to AT&T.

Appendix

A Summary Statistics

Table 10: Summary Statistics

	Main Sample	
Number of Markets	90	
Number of Months	26	
Total Observations	573,121	
Monthly Respondents: Minimum	18,836	
Monthly Respondents: Maximum	24,030	
Average monthly share who own no mobile phone	7.50%	
Average monthly rate of smartphone purchase	1.36%	
	Main Sample (Weighted)	Census
% Female	51.97%	52.06%
% of Adult Population Age 60+	25.54%	24.37%
% Income $100K+	17.22%	15.73%

B Reduced-Form Evidence

First, a regression to show that consumers do indeed respond to network quality differences:

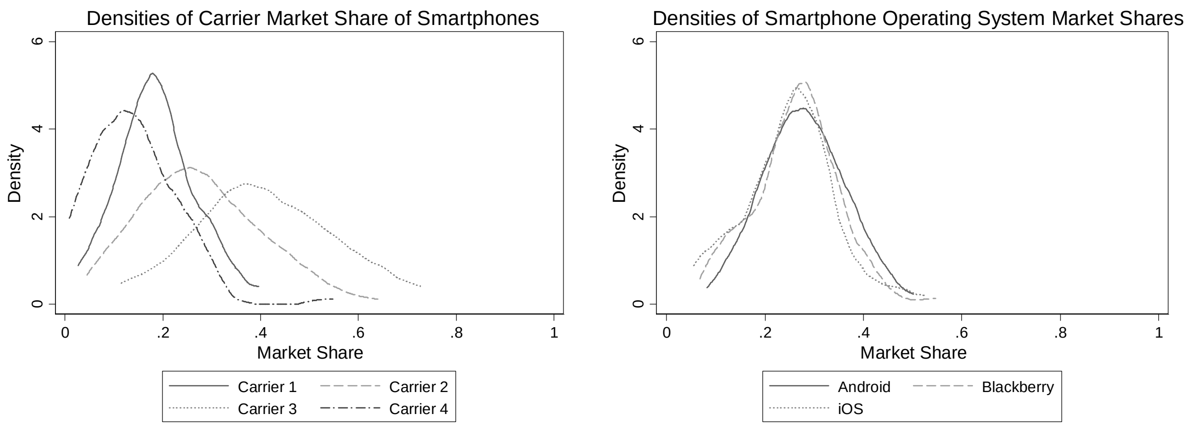
Table 11: Effect of Dropped Calls on Market Share

Independent Variable: Market Share		
Parameter	Estimate	S.E.
Dropped Calls	-0.8393	0.2089
Carrier 1	0.05204	0.01096
Carrier 2	0.1668	0.01460
Carrier 3	0.1398	0.01491
Carrier 4	0.003632	0.01012
Constant	0.1230	0.009399

Results are from an OLS regression. Standard errors are clustered at the market level. The number of observations is 419; the $R^2 = 0.4453$. The data are for the 6th month of survey data. The omitted fixed effect is for Carrier 0, which represents all carriers other than the top four.

The following figure shows raw shares across markets for carriers and smartphones.

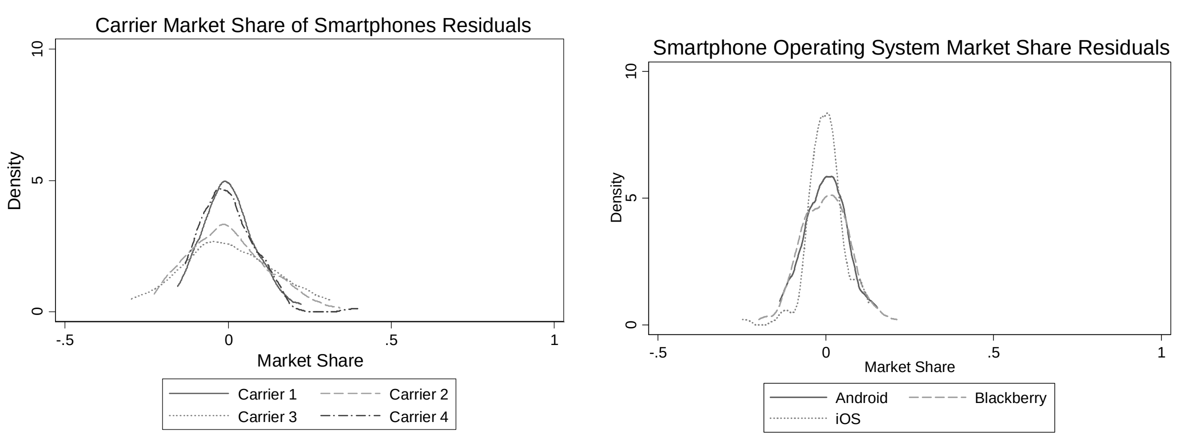
Figure 9: Across-Market Variance in Shares of Carriers vs Smartphones



Note: shares are averaged over final three months of sample to reduce sample noise in smaller markets.

The following figure shows residuals from regressions of the market-level shares of carriers and smartphones on a set of controls, including network quality and income distributions.

Figure 10: Across-Market Residuals from Controlled Regressions



Note: shares are averaged over final three months of sample to reduce sample noise in smaller markets. Controls include income distributions and network quality (for carriers) and AT&T market share (for smartphones).

C Derivation of Hotelling Case

In the Hotelling case, consumer utility from the final good takes the form

$$u_{Ai} \quad = \quad \delta_A - p_A - \theta_i$$

$$u_{Bi} = \delta_B - p_B - (1-\theta_i)$$

Demand for each good at prices $p_{A,}p_B$ is given by integrating over the uniform distribution of types,

$$\begin{aligned}
D_A(p_A,p_B) &= Pr(\delta_A - p_A - \theta_i > \delta_B - p_B - (1-\theta_i)) \\
&= Pr\left(\theta_i < \frac{\delta_A - \delta_B + p_B - p_A + 1}{2}\right) \\
&= \frac{\delta_A - \delta_B + p_B - p_A + 1}{2} \\
D_B(p_A,p_B) &= \frac{\delta_B - \delta_A + p_A - p_B + 1}{2}
\end{aligned}$$

Throughout we will assume that the equilibrium lies in the interior. This is satisfied whenever

$$1 + p_A - p_B > \delta_A - \delta_B \quad > p_A \quad - p_B - 1$$

In the common agency case, downstream firms charge no markups and so upstream firms set the wholesale prices to be the profit-maximizing retail prices:

$$\begin{aligned}
\pi_A^C &= (q_A - c)\, D_A(p_A = q_A, p_B = q_B) \\
\pi_B^C &= (q_B - c)\, D_B(p_A = q_A, p_B = q_B)
\end{aligned}$$

First-order conditions for profit maximization are given by

$$\begin{aligned}
q_A &= \frac{\delta_A - \delta_B + q_B + 1 + c}{2} \\
q_B &= \frac{\delta_B - \delta_A + q_A + 1 + c}{2}
\end{aligned}$$

The equilibrium is therefore given by wholesale and retail prices of

$$\begin{aligned}
q_A^{C*} &= p_A^{C*} = \frac{1}{3}(\delta_A - \delta_B) + 1 + c \\
q_B^{C*} &= p_B^{C*} = \frac{1}{3}(\delta_B - \delta_A) + 1 + c
\end{aligned}$$

Profits to the upstream firms in equilibrium are thus

$$\begin{aligned}
\pi_A^{C*} &= \frac{1}{18}(\delta_A - \delta_B + 3)^2 \\
\pi_B^{C*} &= \frac{1}{18}(\delta_B - \delta_A + 3)^2
\end{aligned}$$

In the exclusive case, the exclusive carrier chooses a price to maximize profits given the wholesale price q_A:

$$\begin{aligned}
\pi_w^E &= (p_A - q_A) D^A (p_A, p_B = q_B) \\
p_A &= \left(\frac{1 + \delta_A - \delta_B + p_B + q_A}{2} \right)
\end{aligned}$$

To avoid double marginalization, Firm A will offer a two-part tariff with wholesale price equal to marginal cost and a tariff equal to all of the profits. The two upstream firms profits are given by:

$$\begin{aligned}
\pi_A^E &= \left(\frac{1 + \delta_A - \delta_B + p_B + c}{2} - c \right) D^A \left(p_A = \left(\frac{1 + \delta_A - \delta_B + p_B + c}{2} \right), p_B = q_B \right) \\
\pi_B^E &= (q_B - c) D^B \left(p_A = \left(\frac{1 + \delta_A - \delta_B + p_B + q_A}{2} \right), p_B = q_B \right)
\end{aligned}$$

Firm B's optimal wholesale price rises now, leading to a higher retail price as well:

$$q_B^{E*} = p_B^{E*} = c + \frac{3}{2} + \frac{1}{2} (\delta_B - \delta_A)$$

Equilibrium profits when A is exclusive and B is not are given by

$$\begin{aligned}
\pi_A^{E^*} &= \frac{1}{32} (\delta_A - \delta_B + 5)^2 \\
\pi_B^{E*} &= \frac{1}{16} (\delta_B - \delta_A + 3)^2
\end{aligned}$$

Finally, consider the case when Firm B is also exclusive, which we will denote by EE. Now two carriers set final retail prices to maximize their profits according to

$$\begin{aligned}
\pi_{wA}^E &= (p_A - q_A) D^A (p_A, p_B) \\
\pi_{wB}^E &= (p_B - q_B) D^B (p_A, p_B)
\end{aligned}$$

Solving, the equilibrium prices they will set as a function of wholesale prices are

$$\begin{aligned}
p_A^{EE*} &= \frac{\delta_A - \delta_B + 2q_A + q_B}{3} + 1 \\
p_B^{EE*} &= \frac{\delta_B - \delta_A + 2q_B + q_A}{3} + 1
\end{aligned}$$

Similar to above, we have that both A and B set two-part tariffs to avoid marginalization, and so set wholesale prices to marginal cost and earn tariff profits of

$$\begin{aligned}
\pi_A^{EE} &= \left(\frac{\delta_A-\delta_B+2q_A+q_B}{3}+1-c\right)D^A\left(\frac{\delta_A-\delta_B+2q_A+q_B}{3}+1,\frac{\delta_B-\delta_A+2q_B+q_A}{3}+1\right)\\
\pi_B^{EE} &= \left(\frac{\delta_B-\delta_A+2q_B+q_A}{3}+1-c\right)D^B\left(\frac{\delta_A-\delta_B+2q_A+q_B}{3}+1,\frac{\delta_B-\delta_A+2q_B+q_A}{3}+1\right)
\end{aligned}$$

Optimizing, the two firms maximize profits, resulting in the following equilibrium:

$$\begin{aligned}
q_A^{EE*} &= c+1+\frac{1}{5}(\delta_A-\delta_B)\\
p_A^{EE*} &= c+2+\frac{2}{5}(\delta_A-\delta_B)\\
\pi_A^{EE*} &= \frac{1}{25}(\delta_A-\delta_B+5)^2
\end{aligned}$$

Firm B's outcome is symmetric to this (swapping δ_A and δ_B).

D Proofs for General Case

The following assumptions stand throughout:

1. Tastes for handsets are independent of tastes for carriers.
2. Handsets A and B are substitutes and their prices are strategic complements.
3. The upstream firms set wholesale prices and tariffs independently (i.e. no collusion is possible).
4. Share functions are continuous and differentiable in all prices. Pricing equilibria exist and are unique.
5. For simplicity, I will assume that the underlying demand system captures downstream "market power" with a parameter $\eta \in [0,\infty)$, such that under common agency, when $\eta = 0$, downstream firms are homogenous as in the above section so that for carrier n, $\frac{\partial s_{An}}{\partial p_{An}} = -\infty$. As η increases, so does $\frac{\partial s_{An}}{\partial p_{An}}$, and in the limit $\frac{\partial s_{An}}{\partial p_{An}} \to \frac{\partial s_A}{\partial p_A}$ as $\eta \to \infty$. This allows us to characterize the limit cases of carrier monopolists ($\eta = \infty$), carriers as homogenous ($\eta = 0$), and cases in-between. The analogous values for cross-partials are that $\frac{\partial s_{An}}{\partial p_{An'}}$ goes from ∞ to 0 as η goes from zero to ∞.

An example of a demand system that would satisfy A5: if consumers have taste draws θ_j for each firm $j = 1..J$, drawn from distributions F_j, and utility from the downstream good of firm j were of the form $u_{ij} = \kappa + \eta\theta_j - p_j$ for some constant κ. This is, in effect, a more general version of a Hotelling model. Note that a demand system of the Logit family would not satisfy this assumption, as downstream firms are always imperfect substitutes in that setting, and so the limit cases are not attainable.

One challenge is that as downstream firms gain more market power, total market power and the equilibrium prices increase, making direct comparisons of equilibrium prices for different levels of downstream market power difficult. For example, when carriers are monopolists, we would expect the carriers to retain some of the joint surplus; it would be unreasonable to expect that handset firms could extract the complete amount of joint surplus. Therefore, to simplify the comparisons, we will assume that when bargaining over the joint surplus, the outside alternative is to have the upstream firms sell handsets directly to consumers. This allows us to characterize the maximum surplus achievable by the upstream firms as the "direct" profits whenever joint profits are greater than that.

We will first analyze the common-agency case, where each carrier $n = 1..N$ offers both handsets. We will look for a symmetric equilibrium outcome. The upstream firms choose the wholesale prices q_{An} and q_{Bn} (and can further extract surplus from a flat tariff). Downstream firms choose final retail prices p_{An} and p_{Bn}, $n \in \{1, ..., N\}$ according to

$$\pi_n = (p_{An} - q_{An})\, s_{An}(p_{An}, p_{-An}) + (p_{Bn} - q_{Bn})\, s_{Bn}(p_{Bn}, p_{-Bn}) \tag{5}$$

Maximizing downstream profits yields two first-order conditions that must be satisfied for both carriers at the optimal retail prices p_A^{C*}, p_B^{C*}:

$$(p_{An} - q_{An}) = \left(-\frac{\partial s_{An}(\mathbf{p})}{\partial p_{An}}\right)^{-1} \left(s_{An}(p_{An}, p_{-An}) + (p_{Bn} - q_{Bn})\frac{\partial s_{Bn}(\mathbf{p})}{\partial p_{An}}\right)$$

$$(p_{Bn} - q_{Bn}) = \left(-\frac{\partial s_{Bn}(\mathbf{p})}{\partial p_{Bn}}\right)^{-1} \left(s_{Bn}(p_{Bn}, p_{-Bn}) + (p_{An} - q_{An})\frac{\partial s_{An}(\mathbf{p})}{\partial p_{Bn}}\right)$$

Notice that the share derivatives must take into account the indirect effect of prices on competing prices, since we have assumed that prices are strategic complements. For example, we have

$$\frac{\partial s_{An}(\mathbf{p})}{\partial p_{An}} = \frac{\partial s_{An}}{\partial p_{An}} + \frac{\partial s_{An}}{\partial p_{Bn}}\frac{\partial p_{Bn}}{\partial p_{An}} + (N-1)\left(\frac{\partial s_{An}}{\partial p_{An'}}\frac{\partial p_{An'}}{\partial p_{An}} + \frac{\partial s_{An}}{\partial p_{Bn'}}\frac{\partial p_{Bn'}}{\partial p_{An}}\right) \tag{6}$$

$$\frac{\partial s_{Bn}(\mathbf{p})}{\partial p_{An}} = \frac{\partial s_{Bn}}{\partial p_{Bn}}\frac{\partial p_{Bn}}{\partial p_{An}} + \frac{\partial s_{Bn}}{\partial p_{An}} + (N-1)\left(\frac{\partial s_{Bn}}{\partial p_{An'}}\frac{\partial p_{An'}}{\partial p_{An}} + \frac{\partial s_{Bn}}{\partial p_{Bn'}}\frac{\partial p_{Bn'}}{\partial p_{An}}\right) \tag{7}$$

where we make use of the fact that we are looking for symmetric equilibria to simplify. Since prices are strategic complements, all derivatives of prices with respect to other prices are positive. We can immediately analyze the limit cases of downstream competition: if carrier demand is perfectly elastic ($\eta = 0$), cross-carrier partial derivatives are infinite, resulting in zero markups. The resulting market outcome is identical to that where the upstream firms compete directly for consumers: handset makers effectively set the final price since q_A and q_B are passed through directly to consumers as p_A and p_B, resulting in equilibrium handset markups under common agency given by

$$\begin{aligned}\left(q_A^{C*} - c\right) &= \left(-\frac{\partial s_A}{\partial p_A}\right)^{-1} s_A\left(\mathbf{p}^{C*}\right)\Big|_{p_A = q_A, p_B = q_B} \\ \left(q_B^{C*} - c\right) &= \left(-\frac{\partial s_B}{\partial p_B}\right)^{-1} s_B\left(\mathbf{p}^{C*}\right)\Big|_{p_A = q_A, p_B = q_B}\end{aligned}$$

Profits for the upstream firms are then

$$\pi_A^{C*} = \left(-\frac{\partial s_A}{\partial p_A}\right)^{-1} N s_{An}\left(\mathbf{p}^{C*}\right)^2 = \pi_B^{C*}$$

In the other limit case where downstream firms are monopolists (and so each carrier effectively serves a different "market"), we have $\eta = \infty$ and zero cross-carrier effects, and are left with only the first two terms of equations 2 and 3. The carrier then maximizes the joint profits as though the upstream firms were colluding (the carrier effectively vertically integrates with both upstream firms); these profits are maximized when handset manufacturers offer marginal cost pricing to eliminate the double-marginalization ($q_A = q_B = c$) and instead extract surplus through a tariff. Total profits are greater than in the previous limit case, although the upstream firms would not be able to extract the full surplus without actually colluding in setting wholesale prices, which we assume is not possible. Following the bargaining assumption made above, the monopolist carrier retains at least the surplus created from internalizing both upstream firms' profits, the upstream firms are left with maximal profits of π_A^{C*} and π_B^{C*}.

In the intermediate cases, we can assume that upstream firms are effectively able to choose the final retail price as they know the markup function used by carriers and are free to set any wholesale price. The combination of variable profits and tariffs can not exceed π_A^{C*}due to the bargaining assumption (i.e. carriers retain surplus generated by their market power).

Now consider the case of exclusivity: handsets A and B are exclusive to carriers 1 and 2, respectively. The equilibrium first-order conditions for optimal prices p_A^{EE*} and p_B^{EE*} are now

$$\begin{aligned}(p_{A1}-q_{A1}) &= \left(-\frac{\partial s_{A1}}{\partial p_{A1}}\right)^{-1}(s_{A1}(p_{A1},p_{B2}))\\ (p_{B2}-q_{B2}) &= \left(-\frac{\partial s_{B2}}{\partial p_{B2}}\right)^{-1}(s_{B2}(p_{A1},p_{B2}))\end{aligned}$$

As η goes from zero to ∞, we have that $\frac{\partial s_{A1}}{\partial p_{A1}}$ goes from $\frac{\partial s_A}{\partial p_A}$ to $\frac{\partial s_1}{\partial p_1}$. The handset competition dominates at low η, and the carrier competition dominates at high η.

Define these markup functions as $m(q_{A1},q_{B2})$ and note that the markup is decreasing in own wholesale price but increasing in opposite wholesale price. Upstream firms, anticipating this markup function, now choose wholesale prices to maximize joint profits, according to

$$\begin{aligned}\pi_A^{EE} &= (q_{A1}+m_{A1}(q_{A1},q_{B2})-c)\,s_{A1}(q_{A1}+m_{A1}(q_{A1},q_{B2}),q_{B2}+m_{B2}(q_{A1},q_{B2}))\\ \pi_B^{EE} &= (q_{B2}+m_{B2}(q_{A1},q_{B2})-c)\,s_{B2}(q_{A1}+m_{A1}(q_{A1},q_{B2}),q_{B2}+m_{B2}(q_{A1},q_{B2}))\end{aligned}$$

Optimizing, we get Firm A's first-order condition given by

$$q_A-c=-m_A+\frac{\left(1+\frac{\partial m_A}{\partial q_A}\right)s_{A1}}{-\left(\frac{\partial s_{A1}}{\partial p_{A1}}\left(1+\frac{\partial m_A}{\partial q_A}\right)+\frac{\partial s_{A1}}{\partial p_{B2}}\frac{\partial m_B}{\partial q_A}\right)}$$

Note that this simplifies to the the first-order condition from the homogenous carrier case if prices are not strategic complements (if there is no positive effect from $\frac{\partial m_B}{\partial q_A}$). Therefore, in the limit case of $\eta=0$, equilibrium prices are higher when prices are strategic complements. Finally, profits for Firm A in this case are

$$\pi_A^{EE*}=\left(\frac{\left(1+\frac{\partial m_A}{\partial q_A}\right)}{-\left(\frac{\partial s_{A1}}{\partial p_{A1}}\left(1+\frac{\partial m_A}{\partial q_A}\right)+\frac{\partial s_{A1}}{\partial p_{B2}}\frac{\partial m_B}{\partial q_A}\right)}\right)s_{A1}\left(p_{A1}^{EE*},p_{B2}^{EE*}\right)^2$$

Exclusivity is optimal iff

$$\begin{aligned}&\pi_A^{EE*} \qquad\qquad > \qquad\qquad \pi_A^{C*}\\ \text{(8)}\quad &\left(\frac{\left(1+\frac{\partial m_A}{\partial q_A}\right)}{-\left(\frac{\partial s_{A1}}{\partial p_{A1}}\left(1+\frac{\partial m_A}{\partial q_A}\right)+\frac{\partial s_{A1}}{\partial p_{B2}}\frac{\partial m_B}{\partial q_A}\right)}\right)s_{A1}\left(\mathbf{p}^{EE*}\right)^2-\left(-\frac{\partial s_A}{\partial p_A}\right)^{-1}Ns_{An}\left(\mathbf{p}^{C*}\right)^2>0\end{aligned}$$

We know that

$$\left(\frac{\left(1+\frac{\partial m_A}{\partial q_A}\right)}{-\left(\frac{\partial s_{A1}}{\partial p_{A1}}\left(1+\frac{\partial m_A}{\partial q_A}\right)+\frac{\partial s_{A1}}{\partial p_{B2}}\frac{\partial m_B}{\partial q_A}\right)}\right) > \left(-\frac{\partial s_A}{\partial p_A}\right)^{-1}$$

holds for all finite η, and that they are equal in the limit as $\eta \to \infty$ (there is no strategic complementarity of prices "across markets", or $\frac{\partial m_B}{\partial q_A} = 0$ in that limit). Also, for any given price vector $\mathbf{p}$, we have that $s_{A1}(\mathbf{p}) = Ns_{An}(\mathbf{p})$ when $\eta = 0$, but $Ns_{An}(\mathbf{p}) - s_{A1}(\mathbf{p})$ increases as η increases. That is, the amount of foregone sales from exclusivity increases as consumers are less willing to substitute between downstream goods. We also know that equation 4 holds at $\eta = 0$. Combining these, we have that equation 4 holds at $\eta = 0$, but that the LHS is decreasing as η increases, and that equation 4 does not hold in the limit as $\eta \to \infty$. Under the continuity assumption, we can apply the intermediate value theorem to get that there exists an η^* at which point equation 4 holds with equality. Therefore, for all values of $\eta < \eta^*$, exclusivity is the profit maximizing strategy.

To address Proposition 2, we start with a model of what a carrier's willingness to pay is. For carrier $n \in \{1,2\}$, the alternative to having handset A exclusively is that carrier n' will have handset A exclusively (I will assume there is a handset B available to both carriers). The equilibrium outcome will be the one that maximizes the joint profits of the exclusive carrier and Firm A.

I first make a simplifying assumption: each carrier chooses only a network access price; handset prices are fixed across carriers at p_h. This simplifies the analysis, and I do not believe this to be a controversial assumption, as in November 2011 when the iPhone is available on three carriers, the device is priced identically across carriers but monthly access fees differ. The two carriers will have identical marginal costs c, and choose their monthly access prices p_n, which creates a final good price for handset h on carrier n of $p_n + p_h$. Carriers choose their monthly access price in the standard profit maximization framework. From now on, p_1 and p_2 represent equilibrium monthly access prices less marginal cost.

Each carrier's willingness to pay is determined by the difference in profits from having exclusivity versus its rival having exclusivity. I denote carrier 1 having exclusivity of handset A by $\chi = 1$, and carrier 2 having exclusivity with $\chi = 2$. For carrier 1, the willingness to pay to Firm A is therefore

$$p_1(\chi=1)\cdot(s_{A1}(\chi=1)+s_{B1}(\chi=1)) - (p_1(\chi=2)+p_A)\cdot(s_{B1}(\chi=2))$$

Similarly, for carrier 2, it is

$$p_2(\chi=2)\cdot(s_{A2}(\chi=2)+s_{B2}(\chi=2)) - (p_2(\chi=1)+p_A)\cdot(s_{B2}(\chi=1))$$

Re-arranging, we have each carrier's willingness to pay having two components: a change in profits from B, and the sales potential of A.

$$[p_1(\chi=1)\cdot s_{B1}(\chi=1)-p_1(\chi=2)\cdot s_{B1}(\chi=2)]+(p_1(\chi=1)+p_A)\cdot s_{A1}(\chi=1)$$

$$[p_2(\chi=2)\cdot s_{B2}(\chi=2)-p_2(\chi=1)\cdot s_{B2}(\chi=1)]+(p_2(\chi=2)+p_A)\cdot s_{A2}(\chi=2)$$

We are assuming that carrier 1 faces more elastic demand from its network. Therefore, at $\beta=0$, we know that the first term for carrier 1 is larger than for carrier 2, and the difference is increasing in β. Further, we know that the second component is larger for carrier 2, since he has a higher quality network, and that this difference is growing in β. Therefore, to establish Proposition 2, we need to show that the 2nd component grows faster in β. This follows form the inclusion of p_A, which is fixed for all β. The price p_A is perfectly inelastic, whereas the equilibrium network prices cannot be, and so there reaches a point at which the limited market achievable by carrier 1 dominates the gains carrier 1 can earn in monthly fees.

E Alternative Logit Approach

The model described in Section 4 is similar to the Pure Characteristics model described by Berry & Pakes (2007), which omits i.i.d. Logit draws for each possible good and opts instead for only random coefficients to rationalize tastes. A Logit approach in this setting would consist of adding an i.i.d. Logit errors to each discounted flow utility U_{imnht} and directly estimating a likelihood for each survey respondent. For example, if we observe a survey respondent that owns an iPhone on AT&T which was purchased 5 months ago, then we know that in the survey month, this consumer's state was a 4-month old iPhone on AT&T with 20 months remaining on contract and an early termination fee of, say, \$155. We also know that in the survey month, this respondent chose to stay with their iPhone instead of switching to another device or network. We could model the Logit probability of this choice, and maximize the sum of the log likelihoods of these probabilities for all observations. Such an approach has two major challenges in implementation:

First, such a setup would not easily allow for unobserved tastes (such as random coefficients) beyond the Logit draw. The reason for this is that unobserved taste vectors would have to be drawn from the conditional distribution based on your state. Put simply, our survey respondent's unobserved tastes are not random this month if they chose to purchase an iPhone 5 months ago. Properly drawing from the conditional distribution would be intractable, and imposing that the distribution of random coefficients is state-independent would be unrealistic.

Second, we do not directly observe switching in the dataset. If I observe a survey respondent who purchased an iPhone this month, I do not know what their state was when they arrived in this decision period: they may have been on contract or not, and they may have had a smartphone or not. One approach to measure the likelihood of this observation would be to look at the empirical distribution of states from the previous month for the given market and determine the likelihood of observing an individual purchase an iPhone this month, given the distribution of states in the previous month. This is feasible, although computationally costly, and relies heavily on the quality of the survey sample from that particular market.

Finally, direct estimation of each survey respondent would involve maximizing a likelihood over approximately 600,000 observations, a non-trivial task. Including random coefficients would increase the computational burden linearly in the number of simulation draws per individual. Even if we were to ignore state-dependence and match aggregate market-level shares for each market and each month, the sample noise is problematic, particularly in smaller markets, and leads to cases of zero shares for some handset-network bundles, whose likelihood is undefined.

Taken together, this is evidence that this dataset does not lend itself to direct estimation and that serial correlation of tastes is an important aspect of this market to capture. For these reasons, I proceed with the model described in Section 4.

F Bias-Corrected Objective Function and Inference

The bias-corrected objective function arises form the fact that, as has been noted before, the objective function

$$Q_{LNS}^{naive}(\theta) = \frac{1}{L}\sum_{l=1}^{L}\left\{\left(\psi_l^0 - \psi_l^{NS}(\theta)\right)^2\right\}$$

where moments are indexed by $l = 1..L$ results in a biased estimate when minimized. This is because minimizing the above has as its first order condition

$$H(\theta) \equiv \sum_{l=1}^{L}\left\{\left(\psi_l^0 - \psi_l^{NS}(\theta)\right)\frac{\partial \psi_l^{NS}(\theta)}{\partial \theta}\right\} = 0$$

which, at the true value θ^0, has a non-zero expectation due to correlation between the simulated moment and its derivative; specifically,

$$H\left(\theta^0\right) = -E\left[Var\left(\psi^{NS}\left(\theta^0\right)\right)\right]$$

The bias-corrected objective function obtains a consistent estimate of this above covariance and subtracts it from the naive objective function, resulting in a consistent estimator.

Confidence intervals are obtained using suggestions from Laffont, Ossard & Vuong (1995). Proposition 3 of the former paper establishes a method of estimating confidence intervals that correct for simulation bias (see pp. 964 for estimating equations). I use this suggestion in the construction of the confidence intervals for the point estimates of the parameters. For the confidence intervals of the counterfactuals, I bootstrap 200 draws from the estimated parameter distribution and report the 5th and 95th percentiles of the estimates.[58]

G Robustness

One attractive feature of this setting is that carriers are not permitted to charge different prices in different markets. With 90 markets of data, I therefore have prices set at a national level but market-level variation in terms of the product quality (dropped calls). Since price is fixed across markets, I do not need to be concerned about price being correlated with market-level variation in products. However, since carriers are not able to vary prices across markets, it is likely that they may vary other factors in response to differences in their product quality in a given market. It is for this reason that I explicitly include a carrier's share of advertising spend in the demand for a "flagship" handset. Another concern may be a carrier's retail presence: I regressed the share of a carrier's customers in a market who reported that they purchased their device from one of the carrier's own retail stores (as opposed to a national chain or online) on the carrier's network quality and found no relationship in the data. This leads me to conclude that carriers are not significantly altering their retail presence in response to their network quality.

[58] For counterfactuals that involve re-computing the price equilibrium, I cannot confirm that the bootstrap method is valid, as I cannot prove that iterating best responses leads to a unique price equilibrium in this model.