THE EFFECT OF MARKET STRUCTURE ON CELLULAR TECHNOLOGY ADOPTION AND PRICING[*]

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Abstract

We analyze how changes in market structure affect the technology adoption and nonlinear pricing decisions of cellular firms, focusing on the time period from 1996, when cellular markets were duopolies, to 1998, when markets experienced varying degrees of entry from personal communications services (PCS) firms. We relate the adoption of digital technology by incumbents and the features of the chosen calling plan menus to the amount of PCS entry in different local markets. Geographic features of these markets contribute to the difficulty of building a sufficiently large wireless infrastructure network, providing effective instruments for endogenous entry decisions. We find that entry spurs incumbents' adoptions of the digital technology and increases the number of plans they offer. Incumbents and entrants spread plans over a broader range of the usage spectrum and lower prices more in markets with more entry. However, high-valuation consumers benefit more than low-valuation consumers as firms offer proportionally more high-usage plans and offer steeper quantity discounts in markets with more entry.

Keywords: entry, market structure, technology adoption, price discrimination, nonlinear pricing, telecommunications

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1. Introduction

We study how market structure affects technology deployment choices and nonlinear pricing strategies in U.S. mobile telecommunications markets in the latter half of the 1990s. Starting out as regulated duopolies, U.S. cellular markets experienced considerable entry after mid-1996 when firms began activating licenses to new spectrum for mobile communications services. By 1998, the geographic markets experienced different levels of entry by these Personal Communication Services (PCS) providers. At the same time, incumbent cellular carriers had the option to transition from analog to digital service with the development of marketable digital transmission technologies.

The successful diffusion of an innovation depends not only on the time of introduction, but also on its subsequent pricing. In information industries, technologies evolve rapidly and firms often price discriminate using menus of nonlinear pricing plans to segment consumers. The extent to which different types of consumers benefit from a new technology depends on the plan choices and their characteristics. This raises the additional question of how competition affects firms' choices of prices and plan characteristics in the wake of technological innovation.

Our paper makes two main contributions. First, we provide empirical evidence on the relationship between market structure and speed of technology adoption. Second, we investigate how firms' nonlinear pricing strategies subsequent to the adoption of a new technology relate to competition. To do so, we use two snapshots, one before and one after PCS entry, of firm- and market-level data on the universe of cellular calling plans.

The mobile telecommunications industry of the late 1990s is an ideal setting in which to study these questions since entry resulted from regulatory intervention and varied across markets for reasons unrelated to firm behavior. A market's geographic features affect the time required to build a network of wireless transmission towers that is sufficiently dense to provide service of a satisfactory quality. These features provide suitable instruments to control for unobserved demand or cost conditions driving both entry decisions and firms' technology adoption and pricing choices. Our econometric framework allows us to separate the effect of market structure on technology adoption from those on pricing, including the indirect effect that adoption has on pricing through the competitive interaction between analog and digital providers.

A primary goal of the theoretical adoption literature has been to examine how competition affects adoption speed. The features of our empirical setting allow us to make specific predictions about this relationship. In our setting, where entrants have pre-committed to enter and adopt the digital technology, the incumbents choose the optimal adoption timing without being able to deter entrants' adoptions. We modify a model by Fudenberg and Tirole (1986) to show that an incumbent adopts sooner under more entry if this entry more adversely affects its profits when it remains with the old technology than moves to the new. Based on characteristics of the cellular markets, the model predicts that incumbents in markets with more entrants should adopt earlier.

Our results confirm this prediction. We find that the presence of additional competitors spurs the technology upgrade both through the adoption likelihood and the marketing intensiveness. In markets with more competition, firms are more likely to upgrade and, if they do, phase out calling plans based on the old technology and introduce calling plans based on the new technology more fully. Consistent with firms engaging in business stealing rather than increased differentiation in response to more competition, we find that competition generally decreases the clustering of contracts and thus that firms spread out their plans more in markets with more entry. This implies a direct effect, through increased business stealing opportunities, and an indirect effect, via technology choice, of entry on the number of plans offered.

Although business-stealing incentives lead firms to increase plan variety for all consumers, these efforts are more intense for high-usage customers. Firms increase the number of plans and spread out plans more for high- than low-usage customers in markets with more entry. These results conform to predictions of a theoretical model of competitive nonlinear pricing (Yang and Ye (2007)) and suggest that in markets like the one we examine, in which horizontal differentiation is relatively low, competition will benefit high-valuation customers relatively more when firms screen customers based on their vertical preferences. High-usage customers also gain more from price decreases due to entry. We apply the approach in Busse and Rysman (2005), modified to account for the endogeneity of entry, to test the effect of market structure on overall price levels and quantity distortions. Consistent with their evidence, we find that while firms reduce prices in general, quantity discounts become larger in markets with more entry. Thus, entry benefited high-valuation consumers more.

Our results have important implications for telecommunications regulation. Regulators often auction off or otherwise allocate licenses for new telecommunications services. In these cases, it is important to consider the effect that the number of licenses will have on the improvement of existing technological standards. For example, in deciding how much spectrum to make available for wireless broadband services, regulators should consider the incentives that ensuing competition will provide to incumbents to improve terrestrial Internet access by phasing out narrowband or upgrading existing broadband technologies. In current auctions for 700 MHz cellular licenses, which will enable higher quality service, the Federal Communications Commission (FCC) should consider how the number of licenses affects the speed with which existing cellular providers improve their offerings.

Our results complement theoretical work (Riordan (1992)) that points out that price and entry regulation influences technology adoption by altering the flow profits of the incumbents. Both suggest that an important consideration of entry regulation should be whether the availability of competitive substitutes likely increases the speed with which incumbents improve their technologies. Our results further suggest that regulators consider the subsequent price competition and its relative effects on consumers with different product valuations.

2. Theoretical Background

Market Structure and Technology Adoption

We provide evidence of market structure's effect on the timing of technology adoption, an area with limited and mixed empirical evidence. Levin, Levin and Meisel (1987) find that food stores with greater market shares and stores in less concentrated markets adopt optical scanners sooner. In contrast, Hannan and McDowell (1984) provide evidence that banks operating in more concentrated markets are more likely to be initial adopters of ATMs, while Karshenas and Stoneman (1993) find that industry concentration does not have a significant effect on engineering firms' decisions to adopt computer numerically controlled machine tools.[1] Difficulties in controlling for unobserved determinants of entry and adoption frequently limit the interpretation of these results. In contrast, the well-defined and regulated nature of entry in our setting yields a controlled setting to resolve the ambiguity in the previous empirical literature and test specific predictions of the theoretical literature.

The theoretical literature has focused on explaining technology diffusion, the sequential adoption of an innovation by firms. Differences in demand, costs, or information across firms may lead them to differing adoption times within a market or across markets (see Hoppe (2002) for a literature review). The literature primarily considers strategic aspects of technology diffusion, examining how the possibility of preemptively adopting a technology to deter or delay entry of other firms affects the speed of adoption.

Seminal work by Reinganum (1981a, b) and Fudenberg and Tirole (1985) (FT) yields inconclusive predictions for the effect of market structure on technology diffusion. Reinganum (1981a) shows that the optimal adoption time depends on the change in payoffs at adoption and provides one example of a payoff specification where lower concentration slows technology adoption. FT (1985), on the other hand, implicitly

[1] Hannan and McDowell (1984), Karshenas and Stoneman (1993), Oster (1982), and Rose and Joskow (1990) investigate the effect of firm characteristics, in particular firm size, on adoption speed. We cannot examine this question because firms' subscriber bases, revenues, or network sizes by market are unavailable.

suggests that increased competition may instead accelerate technology adoption due to the increased business stealing opportunities with a larger number of rivals. The differing predictions of the models arise from their assumptions about the strategic game played between identical firms, which results in pre-commitment equilibria in Reinganum (1981a, b) and equilibria with rent-equalization due to the threat of preemption in FT (1985). Reinganum (1981a) notes that a larger number of competitors has an ambiguous effect on adoption speed. It increases the competitive pressure to adopt early and gain a relative advantage, but also divides the post-adoption market more finely leading firms to wait for further reduction in adoption costs. The FT model adds an additional reason for faster adoption, the ability to delay or deter future adoption, leading them to suggest that competition is likely to speed adoption.

Our setting does not match the FT (1985) or Reinganum (1981a, b) models well. FT (1985) does not allow for pre-commitment to entry or adoption. In our setting, the cellular incumbents anticipate future entry by the PCS firms who have pre-committed to adopt the digital technology, as discussed in Section 3. The incumbents' primary decision is whether to adopt before or after the entrants, but early adoption will not deter either entry or the entrants' technology choices.[2] Reinganum (1981b) considers only two firms, not accommodating analysis of our 1998 market. Because Reinganum's (1981a) model assumes that firms are symmetric, it does not yield predictions for the order of adoption by the firms, the focus of our analysis. An additional departure of this literature from our setting is its focus on process, or cost-reducing, innovations. The new technology that we consider has features of both a product and, to a lesser extent, a process innovation, as outlined in Section 3.

In the Appendix, we modify a subgame of the Fudenberg and Tirole (1986) model to better match the features of our empirical setting and derive predictions for the effect of entry on technology adoption timing. We allow for several entrants who have pre-committed to technology adoption and consider an incumbent's best response to their

[2] The incumbents' ability to delay entry is also limited since the FCC required the PCS license holders to meet specific coverage requirements within a five-year time window to maintain their licenses.

future presence. Analogous to the information in our data, we consider only whether the incumbent's optimal adoption time is prior or subsequent to entry and how that changes with the number of entrants. Focusing on pre-commitment simplifies the analysis relative to FT (1986). We consider only the incumbent's adoption timing as a best response to the entrants' pre-committed strategies, but do not solve for the strategic equilibrium response of entrants. As a result, the incumbent's profit function that determines payoffs at alternative adoption times can be flexible and allow for vertical differentiation between the existing and new technologies.

The results suggest that the incumbent's adoption timing hinges upon the sensitivity to the number of entrants of its post-entry profits when it adopts the new technology relative to when it does not. If its profits on the old technology are dramatically reduced by entry relative to those on the new technology, it is more likely to adopt early. The relationship between the demands for analog and digital service likely conforms to this, suggesting that incumbents should adopt earlier in markets with more entry.

Market Structure and Price Discrimination

Our work also relates to the theoretical literature on market structure and the breadth and curvature of nonlinear pricing schedules, subject of work by Stole (1995), Spulber (1989), Gal-Or (1988), and Oren, Smith and Wilson (1983). A common finding of this work is that increased competition lowers price schedules toward marginal cost, increasing market coverage and reducing quality distortion. Yang and Ye (2007) (YY) present a set-up that relaxes some of the assumptions of the earlier work and most closely resembles our empirical setting. The authors model the choice of contract variety (continuum of price and quality pairs) by horizontally and vertically differentiated, symmetric oligopolists. As in our setting, the firms induce consumer sorting into contracts based on the distribution of consumers' vertical preferences.[3, 4]

[3] The modeling of a continuum of nonlinear contracts, common in the theoretical literature with the exception of Wilson (1993), contrasts with the empirically observed, discrete menu of calling plans. Miravete (2007) provides empirical evidence that a small number of tariffs generates similar gains to a

The YY model predicts a relationship between the number of firms and the vertical variety of nonlinear contracts offered that depends on the degree of horizontal differentiation between firms. An increase in the number of firms when horizontal differentiation is high leads to less contract variety per firm, but to greater contract variety when firms are relatively undifferentiated. This result depends on two opposing effects. As the number of firms increases, each firm is less differentiated from its competitors and requires fewer contracts to span its consumers' tastes, a market size effect. At the same time, with a shrinking market share, each firm has a greater incentive to add contracts to steal share from its competitors, a market share effect. The market size effect dominates when firms are distant in (horizontal) product space because firms have local monopolies over a significant portion of their contracts. When firms are close in product space, the business stealing incentives dominate because the firms directly compete for a significant portion of the consumers.

The YY model also provides an additional means to test the relative magnitudes of the market size and market share effects by comparing the effect of market structure on high- and low-valuation consumers. Firms compete directly for high-valuation consumers because a consumer's strong taste for quality can balance a large distance from a firm in horizontal space, while they hold a local monopoly over lower-valuation consumers. Therefore, if the market size (differentiation incentives) dominate, firms not only contract their offerings overall, but contract them more for high- than for low-end consumers. On the other hand, if business-stealing incentives dominate, firms not only expand offerings overall but expand them more at the high than at the low end. As we describe in Section 3, the cellular industry exhibits low levels of horizontal differentiation, suggesting that business-stealing incentives should dominate, resulting in a more pronounced increase in offerings for high-valuation customers.

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fully nonlinear pricing schedule. YY note that with a fixed cost of offering a contract, firms would offer discrete contracts whose number is positively correlated with the measure of vertical types served. Such fixed costs offer a separate reason for firms to reduce the number of contracts when facing more competitors (see Seim and Viard (2004)).

[4] Johnson and Myatt (2003, 2006) consider an alternative model of nonlinear competition with differentiated products where firms compete along a single dimension of vertical quality.

3. Mobile Telecommunications Markets in the Late 1990s

The U.S. cellular phone industry originated in 1981 when the FCC awarded two licenses per cellular market area (CMA) to provide cellular telephone services in a set of 306 metropolitan markets and 428 FCC-designated rural markets covering the entire country (see Figure 1). The duopoly structure existed until the introduction of PCS.[5] Between December 1994 and January 1997, the FCC awarded 2,074 PCS spectrum licenses in six sequential blocks. The geographic market definition used for PCS spectrum differed from that for cellular markets. Fifty-one Major Trading Areas (MTAs), displayed as bold lines in Figure 1, divided the country into regions the size of multiple cities or states, which were subdivided into Basic Trading Areas (BTAs) of the same size as or slightly larger than the corresponding CMA. We utilize two snapshots of the universe of wireless contracts offered for residential service in the 100 largest CMAs (shown as shaded areas in Figure 1) provided by Kagan World Media to investigate the incumbents' response to entry. The first snapshot is as of February 1996, when all but two markets operated as duopolies[6], and the second as of March 1998.

Concurrently with the allocation of PCS licenses, Nextel Communications entered by transitioning from providing mobile radio services to offering wireless services. Nextel began a national rollout of its service in the Chicago market in September 1996. By 1998, Nextel had entered 71 of the 100 largest cellular markets. Despite Nextel's initial focus on business customers, we treat it as a viable competitor to the cellular incumbents, similar to the PCS entrants.

With the conclusion of the PCS auctions, cellular incumbents therefore face potential entry of one specialized mobile operator and six PCS providers. Two main factors drive the number of competitors actually operating in a given market by 1998. First, due to the

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[5] Cellular pricing under this duopoly structure is the topic of Parker and Röller (1997) and Busse (2000).

[6] The two exceptions are the Baltimore and Washington CMAs, which we dropped from the estimation sample. Both markets experience entry by three firms by 1998.

bankruptcy of several winning bidders in small business auctions, 347 licenses remained initially inactive and were re-auctioned only in April 1999. Second, there is a significant lag between the award of a license and the initiation of service while the carrier builds a network of towers to broadcast signals of sufficient quality to its users' phones.[7] This time lag is commonly referred to as the "build-out" delay. Since Nextel's network is cellular-like and consists of a dense grid of transmitters, similar build-out requirements constrained its national rollout of service. The time it takes to deploy service reflects market characteristics such as the potential subscriber base, density of population, geographic area, and terrain features that affect the size of the required tower network and the difficulty of its construction. These characteristics provide exogenous variation in the number of competitors across markets at a given point in time.

Table 1 shows the entrants' resulting launch dates by quarter for the largest 100 markets over the 1995 to 1998 period. By March 1998, on average 4.31 providers offer cellular or PCS service in a CMA. Across markets, five cities had no entry, 25 cities entry by one firm, 27 cities entry by two firms, 33 cities entry by three firms, and ten cities entry by four firms by 1998.

The networks that the entrants built in local markets used digital technologies. Digital technologies improved the efficiency of spectrum use as well as the quality and reliability of service while allowing for new features such as call waiting and caller ID, introducing vertical differentiation to the service provision. Prior to the introduction of digital technology, firms' differentiation was also primarily vertical due to differences in the quality of service in the local calling area, but had few horizontal elements apart from branding. As of 1998, digital service had a limited coverage area and was frequently restricted to the user's local calling area since the providers' uses of four different technology standards increased the chance of inoperability.[8] Initially, therefore, analog service continued to be attractive to low-usage customers or customers who traveled

[7] The FCC required PCS licensees to meet specific coverage requirements, amounting to providing adequate service to at least between 25 and 33 percent of the market's population within five years.

[8] The cellular and PCS providers used one of three digital technology standards, CDMA, TDMA, or GSM. Nextel used Motorola's digital iDEN technology.

frequently outside their operable region. With the increased diffusion of digital technologies, however, demand for digital service quickly exceeded demand for analog service, with approximately fifty percent of subscribers using digital technologies by late 1999 (Cellular Telecommunications and Internet Association (2000)).

The incumbents exclusively employed analog or, in rare cases, immature digital technologies in 1996 and could choose to upgrade their existing analog networks to digital. Adding digital capabilities to an existing network generally involved minimal hardware additions at the towers along with software upgrades and a significant amount of system optimization. Frequently, incumbents did not require any additional towers to provide digital service, eliminating the zoning and other difficulties in identifying new tower locations that the PCS entrants faced. Cellular incumbents were thus able to roll-out digital service quickly in response to changes in demand or supply,[9] allowing us to characterize the upgrade as an adoption decision followed by a fixed, brief implementation time.

The timing of and approach to digital deployment varied significantly across incumbents. By 1998, 42 percent of all incumbent plan families were digital calling plans; however, only eight percent of providers upgraded their full set of analog plans to digital within a given market.[10] Thirty-four percent of providers had not yet begun digital deployment by 1998. The remaining 59 percent of providers gave customers within a given market a choice between analog and digital technology by offering two sets of calling plans.

The calling plans consist of three-part tariffs for wireless service in the local calling area. During the sample period providers generally held licenses to only a small number of markets. Of the 24 cellular providers in the top 100 markets in 1996, fifteen firms operate licenses in at most five of the top 100 cellular markets and only five carriers offer service in more than fifteen markets. Due to the resulting costs for paying other providers to

[9] See Meyers (1997) for a more detailed description of the digital upgrade process.

[10] The FCC's rules require that all incumbent cellular carriers continue to provide analog service through 2008. However, the carriers are not required to offer or market new analog service plans. In contrast, other mobile telephony carriers such as the PCS providers are not required to provide analog service.

terminate or originate calls outside their network, providers offered only local calling plans during the sample period.[11]

Table 2 shows that a menu of calling plans offered by the incumbents in 1996 consisted of, on average, 5.89 individual analog plans, ranging across providers from three to eight plans. By 1998, incumbents had introduced 128 digital plan families across the 98 markets, while continuing to offer 178 analog plan families. Plan families denote a given provider's set of plans that differ in their fixed fee and number of included peak-minutes, but have a common service technology and share other features, such as calling area and contract duration. Relative to 1996, the number of plans in an analog plan family decreased by 0.07 on average; however, the standard deviation of 1.92 plans reflects an uneven adjustment. A large fraction of providers offered both analog and digital plans simultaneously, with their digital calling plan families consisting of 5.06 plans on average. Table 2 also demonstrates the variation in fixed fees and included minutes across plans in 1998.[12]

This variation, together with the variation in entry and the clear definition of markets in this industry yield an attractive setting to test the effect of market structure on technology adoption timing and price discrimination strategies.

4. Econometric Model

To determine how entry affects technology adoption timing and the choice of calling plan variety, we use several measures of calling plan variety. First, we use the change between 1996 and 1998 in the number of calling plans incumbents offer to test whether incumbents respond to the changes in competition by introducing additional calling plans,

[11] With the gradual build-out of larger networks, carriers introduced calling plans with larger regional or national calling areas subsequent to our sample period. AT&T Wireless introduced a national plan without roaming or long-distance charges in May 1998.

[12] The data include detailed calling plan descriptors, which confirm that changes in the menu of plans reflect the introduction or elimination of distinct calling plans. We focus on two key features of cellular contracts, the plan's monthly fixed fee and the number of included peak-minutes. Along these two dimensions, the plan offerings differ significantly within each plan family.

either directly by adding plans to plan families or indirectly by replacing or complementing existing analog offerings with digital offerings. By considering changes in the number of plans, we remove any firm- and market-specific unobservable determinants of the incumbents' plan introduction strategies. Second, we investigate the effect of market structure on second-degree price discrimination in detail by studying the incumbents' and entrants' placement of calling plans across the usage spectrum. We use Herfindahl measures, defined in Section 5, to summarize the placement of calling plans. Third, we test whether increases in the number of competitors intensify competition for high-valuation customers as predicted by the YY model, using the share of contracts targeting high-usage customers and the extent of quantity discounting. For the detailed price discrimination tests we include both entrants and incumbents to increase the number of observations and focus on levels since all entrants had zero plans in 1996.

Our econometric tests relate each of these measures to the competitive environment, controlling for the possible endogeneity of entry, unobserved firm and market factors that affect both adoption and plan-choice decisions, and the simultaneous choice of technology and plan variety. Endogeneity arises if firms choose to build out less competitive markets first, relevant features of which might be incumbents' pricing strategies or the attractiveness of implementing digital technology. The build-out delay that occurs between license award and service activation discussed above suggests instruments to control for this potential endogeneity. We employ a full-information maximum likelihood (FIML) procedure that jointly estimates a system of equations for the endogenous explanatory variable, number of entrants, and the two choice variables, plan variety and the incumbents' adoption of the digital technology.

We specify the firms' choice of plan variety as:

$$\begin{aligned} Variety_{imt} &= \alpha^P + \beta_1^P Prov\_Tech_{im} + \beta_2^P Plan\_Type_{im} \\ &\quad + \beta_3^P \left(Prov\_Tech_{im}\right)\left(Plan\_Type_{im}\right)\left(Entrants_m\right) + \beta_{\geq 4}^P \, \mathrm{X}_{im}^P + \varepsilon_{imt}^P \,, \qquad (1) \\ &\equiv f^P\left[\alpha^P, \beta^P, Z_{imt}^P\right] + \varepsilon_{imt}^P \end{aligned}$$

where $Variety_{imt}$ is the measure of calling plan variety under consideration (change in the number of plans between 1996 and 1998, Herfindahl index of plan placement in 1998, share of high-usage plans in 1998, curvature of the nonlinear pricing schedule in 1998) for firm i in market m for technology t, $Prov\_Tech_{im}$ is a dummy variable indicating whether firm i offers analog-only, digital-only, or mixed technologies in market m in 1998, $Plan\_Type_{im}$ indicates whether firm i's plan in market m is analog or digital, $Entrants_m$ is the number of PCS entrants in market m by 1998, and X_{im}^P is a vector of control variables for firm i and market m. β_3^P isolates entry's effect on the plan variety measure by technology and plan type.

The specification controls for market demographics that might affect firms' choices of plan variety and uses firm fixed-effects to control for firm-specific differences in the response to entry. Following earlier studies of the cellular industry, such as Busse (2000) and Miravete and Röller (2004), we capture the demand for mobile telecommunications services by the market size (population) and demographic variables, including mean commuting time, household income, and educational attainment. Average commuting time in minutes is a crude measure of the additional value of a cellular phone to frequent drivers. Since some of the measures of plan variety may reflect demand heterogeneity, rather than demand size, we also compute Herfindahl-type indices for the demographic variables in each market, representing the probability of two randomly selected MSA residents falling into the same demographic category.[13] Table 2 provides descriptive statistics for the variables and Table 3 summarizes the variables and their sources.

We similarly control for firm and market factors that might affect the incumbents' incentives to adopt the digital technology. Since the entrants pre-commit to the digital technology, we do not include their choice in the econometric model. We specify:

[13] The incumbents' choice to introduce calling plans may reflect growth in market demand. Market-specific changes in the cellular subscriber base are unfortunately not available for all markets in our sample.

$$\begin{aligned} Digital_{im} &= \alpha^D + \beta_1^D Entrants_m + \beta_2^D \% \geq BA_m + \beta_3^D Commute_m + \beta_4^D Pop_m + \\ &\qquad \beta_5^D Income_m + \beta_6^D National_i + \beta_7^D Local_i + \varepsilon_{im}^D \\ &\equiv f^D\left[\alpha^D, \beta^D, Z_{im}^D\right] + \varepsilon_{im}^D \end{aligned} \quad , \qquad (2)$$

where $Digital_{im}$ equals one if firm i adopted digital technology in market m by 1998 as indicated by marketing a digital plan family, $\% \geq BA_m$ is the percentage of households in market m whose head of household has more than a bachelor's degree, $Commute_m$ is the average commuting time in market *m*, Pop_m is the population in market *m*, $Income_m$ is the average household income in market *m*, and $National_i$ and $Local_i$ indicate whether the firm operates a large or small network of markets, defined as more than fifteen and five or fewer markets respectively. We also include provider fixed-effects. β_1^D isolates the effect of entry on the incumbents' adoption choices.

To control for the endogeneity of entry, we rely on measures of market size, density, and geography that affect the build-out delay across markets. Specifically, we let:

$$\begin{aligned} Entrants_m &= \alpha^E + \beta_1^E Pop_m + \beta_2^E Pop_m^2 + \beta_3^E Area_m + \beta_4^E Area_m^2 + \beta_5^E \% \, City_m + \\ &\qquad \beta_6^E AvgElev_m + \beta_7^E StdElev_m + \varepsilon_m^E \\ &\equiv f^E\left[\alpha^E, \beta^E, Z_m^E\right] + \varepsilon_m^E \end{aligned} \quad . \qquad (3)$$

Pop_m captures the market's potential subscriber base, which has an ambiguous effect on entry. A larger potential market attracts entry, while making it more difficult to satisfy build-out requirements. We collect information on the CMAs' average $\left(AvgElev_m\right)$ and standard deviation $\left(StdElev_m\right)$ of elevation as a measure of terrain variability and thus geographic impediments to constructing a tower network. Last, we include the market area $\left(Area_m\right)$ and percent of the market contained in cities as a measure of the degree of urbanization $\left(\% \, City_m\right)$, which would facilitate meeting build-out requirements.

Our estimation accounts for the discreteness of our data. The technology adoption decision is a binary choice, while entry is an ordered choice ranging from zero to four. Among our plan variety measures, the plan introduction decision is an ordered choice ranging from –6 to 9, while the others are continuous. We estimate a system of three nonlinear equations using FIML, building upon Ackerberg and Botticini (2002)'s two-equation specification. The Appendix contains details of the approach. We model the technology adoption choice as the probit model:

$$Digital_{im} = \begin{cases} 1 & \text{if } f^D\left[\alpha^D, \beta^D, Z^D_{im}\right] + \eta^D_{im} > 0 \\ 0 & \text{otherwise} \end{cases}, \tag{4}$$

the entry equation as the ordered probit model:

$$Entrants_m = \begin{cases} 0 & \text{if } f^E\left[\alpha^E, \beta^E, Z^E_m\right] + \eta^E_m < C^E_1 \\ j & \text{if } C^E_j < f^E\left[\alpha^E, \beta^E, Z^E_m\right] + \eta^E_m < C^E_{j+1}, j = 1,2,3 \\ 4 & \text{if } C^E_4 < f^E\left[\alpha^E, \beta^E, Z^E_m\right] + \eta^E_m \end{cases}, \tag{5}$$

the plan choice equation as the ordered probit model:

$$\Delta\, Plans_{imt} = \begin{cases} -6 & \text{if } f^P\left[\alpha^P, \beta^P, Z^P_{imt}\right] + \eta^P_{imt} \le C^P_{-5} \\ l & \text{if } C^P_l < f^P\left[\alpha^P, \beta^P, Z^P_{imt}\right] + \eta^P_{imt} \le C^P_{l+1}, l = -5,\ldots,8 \\ 9 & \text{if } C^P_9 < f^P\left[\alpha^P, \beta^P, Z^P_{imt}\right] + \eta^P_{imt} \end{cases} \tag{6}$$

and the remaining variety measures as:

$$Variety_{imt} = f^P\left[\alpha^P, \beta^P, Z^P_{imt}\right] + \eta^P_{imt}. \tag{7}$$

We assume that η^D_{im}, η^E_m, and η^P_{imt} are distributed according to a trivariate normal distribution with the variances of the discrete variables normalized to one. We assess parameter significance using a bootstrap sample of 100 replications and control for non-random clustering of unobservables by firm.[14]

5. Results

Our results consist of a series of estimates for the system of three equations described in Section 4, using alternative measures of firms' nonlinear pricing strategies in addition to the entry and digital adoption variables. The system of nonlinear equations (4), (5), and (6)/(7) is identified even without standard instruments because of the nonlinearities of the ordered probit equation for entry. Since identification derives in part from the functional form assumptions for the error terms, we also estimate ordinary least squares (OLS), two-stage least squares (2SLS), and unreported limited information maximum likelihood[15] specifications of the plan variety and adoption equations. We discuss the OLS and 2SLS results in detail for the first model, using the change in the number of plans, but for the sake of brevity, do not display linear equation estimates for the remaining specifications. We begin with a discussion of the determinants of firms' adoption decisions.

Technology Adoption

Column 1 of Table 4 displays OLS results of the adoption equation. Entry positively affects adoption. Incumbents are also more likely to adopt the new technology in markets with greater populations or higher income and if they have a larger potential network. To control for the possibility of endogenous entry into markets, we use 2SLS, with Equation (3) as the first stage. The entry regression has an adjusted R^2 of 0.50 indicating that the instruments are predictive of the number of entrants. Column 3 of Table 4 shows second-

[14] For each bootstrap sample, we draw firms from the set in our sample and include the full set of plan families each firm offers across their markets. We add firms until the number of observations is at least as large as the number of observations in the actual data set and the bootstrap sample contains at least one observation for each level of the discrete variables.

[15] The limited information maximum likelihood estimates use methods in Kelejian (1971). The estimates obtained from this procedure are similar to the FIML estimates and are available upon request.

stage results for the technology adoption equation. Number of entrants now has a larger statistical and economic effect on incumbents adopting the digital technology, suggesting that there are unobserved factors that affect entry and technology adoption oppositely. For example, a large number of traveling professionals in a market creates high demand for wireless services and makes it an attractive entry target, but also places a premium on compatible networks outside the local calling area, providing an incentive for incumbents to delay the digital upgrade due to its incompatibility with outside networks. The effects of commuting time, population, and income are no longer significant while adoption continues to be positively correlated with the scope of the incumbents' network.

To allow for the discreteness of the data we estimate a nonlinear instrumental variables (IV) FIML model of the adoption equation. The effect of the number of entrants on technology adoption, shown in the middle columns of Table 5, is almost identical to the 2SLS results. The right-hand columns of Table 5 contain results from FIML estimation of the system-of-equations specification that controls for any common, unobserved factors that affect both adoption and plan-choice decisions. Entry has a very significant and positive effect on digital adoption. The effect is also economically significant. Each additional entrant increases the probability of adoption by ten percentage points. The results indicate a U-shaped effect of firm scope on digital adoption, with large- and small-scope firms being more likely to adopt than medium-scope firms. Large-scope firms may benefit from economies of scale in implementing digital technology due to cost savings from learning-by-doing or quantity discounts in equipment purchases. On the other hand, small-scope firms are likely to attract consumers who travel less and are therefore less affected by incompatibility of different digital technologies outside their locale, providing greater demand-side incentives for small-scope firms to adopt earlier. Firms in more highly educated markets are less likely while those in more populous or wealthy markets are more likely to adopt the technology.

These results are consistent with those of Hamilton and McManus (2005) that firms in competitive markets are more likely to have adopted a new technology earlier than those in monopoly markets. Our papers provide a complementary picture of the role of technology adoption in firm behavior. While we focus on how technology adoption affects adopters' pricing, their work focuses on the effect of technology adoption on adopters' market shares and ability to deter entry.

Our results are also consistent with predictions from the model in the Appendix. The model predicts that the incumbent is (weakly) more likely to adopt prior to entry when its post-entry profits under the old technology are more sensitive to the number of entrants than its profits under the new technology. While we do not observe demand in our data, the relationship between the demands for analog and digital service likely conforms to these conditions. As discussed in more detail in the Appendix, the demand for the digital technology quickly overtook that of analog, suggesting that post-entry profits on the analog service were more adversely affected than that of digital service.

Although we continue to estimate all three equations jointly in the remaining plan variety models, we relegate the results for the digital adoption equation to the footnotes of the tables going forward. In all of the specifications using our full sample, entry has a positive and significant effect on digital adoption and the marginal effects all range between nine and fifteen percentage points per entrant.

Nonlinear Pricing – Plan Introductions

We begin our analysis of the effect of competition on plan variety by looking at incumbents' incentives to introduce additional plans. Our results are consistent with incumbents increasing calling plan variety for new or continuing technologies and phasing out calling plans for obsolete technologies more heavily in markets with more competitors.

Column 2 of Table 4 displays the results of estimating the plan change equation using OLS. Entry has a significant effect on the change in the number of plans offered by both analog-only and mixed-technology providers. An additional entrant in a market is associated with a decrease of 0.44 analog plans and an increase of 0.48 digital plans for a mixed-technology incumbent. Incumbents thus phase out more analog plans and introduce more digital plans in markets where they face more entrants. The effect is also economically significant given a mean of 5.89 plans in a market in 1996 and a mean of 2.16 entrants in a market. Analog-only incumbents introduce 0.50 plans for each additional entrant. The effect of entry on digital-only incumbents is positive but insignificant, perhaps because there are only fifteen observations to identify this effect. Of the demand heterogeneity variables, only income heterogeneity has a significant negative effect on the change in the incumbents' calling plan portfolio.

Column 4 of Table 4 shows the 2SLS results. We again find that mixed providers increase their digital and decrease their analog offerings in markets with more entry. The main effect of controlling for endogeneity is that entry's effect on plan offerings by analog incumbents changes sign and becomes insignificant. All of the entry effects decline in magnitude, implying that there are omitted variables associated with additional entry and increased plan offerings. These could include growth in cellular demand or its heterogeneity, which would lead firms to offer a larger variety of plans and at the same time attract entry.

The left-hand columns of Table 5 show the results of a nonlinear IV FIML specification. The effect of the number of entrants on the plan choices of mixed providers is similar in magnitude, but much more significant, than the 2SLS results. Greater heterogeneity in household income and commuting time are associated with greater plan variety. The results from the system-of-equations FIML specification shown in the right-hand columns of Table 5 are similar. Two demand heterogeneity proxies are significant although their economic effects are small. A one standard deviation increase in commuting time concentration decreases the number of plans in a market by 0.08 plans and in income concentration by 0.16 plans. Mixed-technology incumbents introduce more digital plans and phase out more analog plans in markets with more entrants and both effects are highly significant. These incumbents introduce 0.43 digital plans and remove 0.45 analog plans for each additional entrant in the market. The results for single-technology providers are insignificant. These results are complementary to work by Borzekowski, Thomadsen and Taragin (2006) who find that direct-mail-marketing firms offer a larger number of distinctly-priced selection criteria, and thus price-discriminate more finely, in markets with more competitors.

An innovation is only useful if adopted and marketed by firms. Our estimates allow us to quantify how adoption affects a firm's subsequent marketing of the digital technology, controlling for entry. Specifically, a firm in an average sample market without entry offers 3.1 more plans when it fully replaces its analog service by digital service. Given that the mean number of plans in an analog plan family is 5.89 in 1996, adoption has an economically significant effect on plan variety, even in the absence of entry.

Our model also allows us to calculate the total effect of entry on plan introductions. Entry not only has a direct but also an indirect effect. Increased entry increases the likelihood that an incumbent transitions to the digital technology, leading it to phase out some analog plans but introduce even more digital plans. For example, in the average market in our sample, moving from no entry to the average level of entry increases the probability of adoption of the digital technology by 21 percentage points. Transitioning from analog-only to a mixed technology provider in turn leads to a decrease of 1.3 analog and an increase of 3.8 digital plans for a net increase of 2.5 plans.

Besides the market size and market share effects identified in YY, theory predicts that a higher fixed cost of offering a plan should counter incentives to offer more calling plans in response to entry. These could be costs to the firm for development, marketing, or administration or time spent by consumers understanding the different plans. In unreported results, we investigate the role of fixed costs on plan offerings using data from the Marketer's Guide to Media (1998) on the market-level cost of radio advertising time as a proxy for firms' marketing costs. The direct effect of marketing costs on the number of plans is negative and significant for plans that the firms promote actively, consistent with firms offering fewer plans in markets with higher costs of doing so. We turn now to our results on the relationship between entry and other nonlinear pricing measures.

Nonlinear Pricing – Overall Placement of Plans

Our price discrimination results thus far are consistent with increased competition manifesting itself as business stealing through plan introductions rather than increased differentiation. To shed further light on this, we test the effect of entry on the placement of calling plans. If firms spread out their plans more with more entry then this would be consistent with efforts at business stealing. We use a Herfindahl index based on the share of minutes "allocated" to each plan to capture the placement of plans across the usage spectrum. For a plan-family with n plans, the lowest possible value of the Herfindahl-index would be $1/n$ if all plans were equally spaced and the largest possible value would be 1 if all plans were identical.

To calculate the plan's allocated minutes we order plans by their number of included peak minutes (the "allowance") and take the difference between its allowance and that of the prior plan.[16] To make the Herfindahl index comparable across plan families, we control for the number of plans per family in two ways. Our main measure normalizes the Herfindahl by dividing it by the Herfindahl that would result from equal spacing of plans $(1/n)$. We include the entrants' and the incumbents' plan families in 1998, or 506 plan families, excluding fifteen single-plan, two-part tariff families. Our secondary measure utilizes a sub-sample of plan families with five to seven plans, reducing the number of observations to 335. Summary statistics for both measures are in the top panel of Table 6.

We employ the same specification as for our plan change specification except we use levels rather than heterogeneity measures for the demographic variables to capture how overall demand affects firms' choices of plan spacing. Competition has a significantly

[16] As a robustness check, we replicate our results using as an alternative measure of allocated minutes the number of minutes for which a particular plan represents the cost-minimizing option in the plan family. The disadvantage of this measure relative to the allowance-based measure is that it requires an assumption about the maximum usage of consumers, which we restrict to 1,000 minutes. The results using the normalized Herfindahl measure are similar to the ones in Table 7 in terms of both magnitude and significance of the coefficients.

negative effect on the normalized measure for all plan family types, except for digital offerings by mixed-technology providers. These results, shown in the left-hand columns of Table 7, are also economically significant. As a share of the mean across all plan families, an additional entrant decreases the normalized Herfindahl by 6.4% to 12.7% depending on plan family and provider technology. This is consistent with business-stealing incentives overpowering differentiation incentives with increased competition. Firms spread their plans out over a wider swath of customers when they compete against more firms.

The results using the secondary measure, shown in the right-hand columns of Table 7, are similar in significance and magnitude for plan families in single-technology offerings. For this sub-sample, the average Herfindahl is equal to 2.8 equally-spaced plans. One entrant increases this to 3.3 equally-spaced plans and two entrants to 4.1 for an analog plan family. For digital families, one entrant would increase this to 3.1 and two entrants to 3.4. The results in mixed-technology offerings are not significant, possibly because there are very few observations. These results also confirm that the earlier plan change results are not due to counting very similar plans as fully distinct.

Nonlinear Pricing – Heterogeneous Impact

For digital plans, we find that firms increase the number of plans offered in markets with more entry (see Table 5). In the YY model, this arises if firms compete in a regime of relatively low horizontal differentiation.[17] Firms are sufficiently similar such that with more entry, the incentive to expand market share (by decreasing plan clustering) exceeds the incentive to increase prices to loyal customers (by increasing plan clustering). The YY model predicts that this business stealing incentive manifests itself at the high-end of the quality spectrum, or here usage spectrum, where the strong tastes of high-valuation consumers overcome the horizontal differentiation between the firms.

[17] The analog plan results are consistent with firms competing in a regime of relatively high horizontal differentiation. However, their pricing also reflects the technology's phasing-out, which likely overwhelms the pure differentiation effects.

To test this prediction, we relate measures of the share and concentration of "high-usage" plans in a plan family to the same independent variables as in our tests of overall plan variety (summary statistics for the measures are in the bottom panel of Table 6). We designate a calling plan as high-usage if the number of included minutes is greater than 180, the median allowance across all plans in our sample. The results using the share of high-usage plans are shown in the left-hand columns of Table 8 and are consistent with theoretical predictions of the YY model. The share of high-usage plans increases significantly with the number of competitors for all provider-types, except digital plan offerings by mixed technology providers. An additional competitor increases the share by two to six percentage points, depending on the plan family and provider type, compared to an average share of 55%. This is a large effect given the number of competitors ranges from two to six.

To test competition's effect on clustering among high-usage plans, we again employ a Herfindahl index, normalizing it by the index if all plans above the median were equally spaced. Theoretically, this measure ranges from a minimum of one when all plans are high-usage and equally spaced, and j, when all j plans above the median are identical.[18] In our data, this measure ranges from one to 3.02. The results are shown in the middle columns of Table 8. Entry has a negative and significant effect on the normalized Herfindahl index for all plan families but digital ones offered by mixed-technology providers. Relative to the average normalized Herfindahl index across all plan families (1.33), each additional entrant reduces the ratio by 3.1% to 11.2% depending on the plan family and provider type. Competition leads firms to spread out their high-usage plans more in markets with more entry, targeting a wider spectrum of high-valuation customers.

As a robustness check, we control for different-sized plan families by using the non-normalized Herfindahl and restricting the analysis to plan families with five to seven plans. The results, displayed in the right-hand columns of Table 8, are qualitatively

[18] The Herfindahl in the numerator is undefined when there are no high-usage plans. This accounts for the seventeen observations we lose when using this measure.

similar. For this sub-sample, the average Herfindahl above the median is equal to 2.1 equally-spaced plans. One entrant would increase this to 2.3 equally-spaced plans for an analog plan family and to 2.4 for a digital plan family. The results for mixed-technology offerings are not significant, although there are very few observations.

Nonlinear Pricing – Quantity Discounting

The last aspect of firms' plan variety choices we investigate is whether competition not only increases the number of offerings targeted at high-valuation customers, but also reduces their prices proportionally more than those paid by low-valuation customers. We follow the approach of Busse and Rysman (2005) (BR) to assess the effect of competition on quantity discounting.[19] This is equivalent to measuring the response in price-cost ratios to changes in competition if, as is likely in our setting, the marginal cost of providing service to low- versus high-valuation customers does not vary with competition. BR suggest that one empirical test of this relationship is whether the price schedule's curvature changes with the number of competitors. We follow their approach in specifying the log price charged by provider i in market m for q_j minutes of service on technology t, P_{ijmt}, as:

$$\ln(P_{ijmt}) = \alpha_{imt} + \beta_{imt} \ln(q_j) + \varepsilon_{ijmt}, \tag{7}$$

where α_{imt} captures differences in cost or demand levels across providers and markets and β_{imt} the curvature of the price schedule. A value of one for β_{imt} corresponds to linear pricing, $\beta_{imt} < 1$ to quantity discounting, and $\beta_{imt} > 1$ to quantity premia.

To estimate Equation (7), we construct a grid of usage levels in ten-minute increments. We compute the minimum total price at each level across all calling plans in the plan

[19] Related work on second-degree price discrimination includes McManus (2007) who provides empirical evidence for the "no distortion at the top" prediction of theoretical models of nonlinear pricing using data on quantity discounting in coffee shop pricing.

family, thus constructing the lower envelope of prices in the family. The underlying assumption, as in Miravete and Röller (2004), is that consumers choose the optimal plan for their usage, ruling out consumption on dominated plans. We bound the usage grid at 1,000 minutes. Individual-level usage data for 1999 and 2000 obtained from TNS Telecoms indicate a usage level of 985 minutes for the 99th percentile of consumers. Since our data cover an earlier period, a cutoff of 1,000 minutes represents a reasonable estimate for maximum usage. Our results are robust to using a larger cutoff.

We use a two-stage procedure. We first obtain the price schedule parameters α and β for every technology-provider-market combination by separately estimating Equation (7) for each plan family using OLS. This generates a distribution of estimates for α and β based on 521 plan families, summarized in Table 9. All plan families exhibit quantity discounting, with digital plan families offered by incumbents and entrants exhibiting more discounting than analog plan families. In the second stage, we follow Miravete and Röller (2004) in assessing how the estimated curvature of the pricing schedule changes with competition by using the estimated curvature parameters β as a plan-variety measure in Equation (7).[20]

The results of the FIML estimation of equations (4), (5), and (7), shown in Table 10, suggest that the increased number of plans targeting high-usage customers result in lower prices.[21] Competition increases the magnitude of quantity discounting, especially by analog- and digital-only providers. An additional firm in the market decreases the curvature of the nonlinear pricing schedule by 0.039 for analog-only providers and 0.027

[20] The second stage of our estimation departs from BR's procedure. They incorporate the estimated standard deviation of the residuals of each plan family's price-quantity regression into an FGLS procedure using all price observations. The FGLS procedure does not control for the endogeneity of entry, which as BR acknowledge, results in upper-bound estimates of the effect of competition on the curvature. The FGLS estimates for our data were consistent with a range of responses to entry from quantity discounting to premia.

[21] We verified that prices fall overall with increased competition. We regressed the minimum price for 180 minutes of usage for all plan families in 1996 and 1998 on the same variables as in Equation (8) plus a year dummy. Prices fall with entry although not all the coefficients are significant. The results are robust to using 2SLS to control for endogeneity of entry and to using minimum prices at 500 minutes.

for digital-only providers, relative to an average curvature of 0.627 and 0.482, respectively.

Overall, we find that introducing additional competition into cellular markets profoundly changed firms' nonlinear pricing practices. Incumbents adopting the digital technology phased out analog plans in favor of even more digital plans. Incumbents and entrants spread out plans more and reduced prices, particularly for high-valuation consumers, consistent with theoretical predictions of competitive second-degree price discrimination in markets with low degrees of horizontal differentiation.

6. Conclusion

We examine the effect of entry on firms' responses to the development of a new technology in a setting that allows us to control for unobservable determinants of both the market structure and the behavior of interest. In contrast to previous work, we are able to examine the chain of events from adoption through to marketing of the new technology. We find economically significant effects of market structure on both.

Our results are consistent with lower concentration speeding up technology adoption and stimulating marketing of the technology. Incumbents in markets with more competitors are more likely to transition from analog to digital transmission technologies. This is consistent with cellular incumbents who anticipated that significant entry of digital competitors would largely eliminate the market for analog service. These incentives exceeded that of waiting until the cost of deploying the technology fell further.

Lower concentration is also associated with firms marketing the new technology more aggressively both in number of plans offered and targeting a wider swath of the usage spectrum. This is consistent with firms' incentives to "fill the calling plan space" to steal customers whose tastes were not closely served by their existing menu of calling plans, despite the narrower segmentation of the market among firms. This incentive for business stealing is greatest for high-valuation customers as firms compete most fiercely for customers who prefer large volumes of minutes.

Our results on the interaction between firms' pricing strategies and technology adoption motivate a more detailed analysis of the effect of technology adoption on subscribers' quantity responses and therefore consumer welfare, requiring more detailed data than is available in the current setting. Such quantity data would also allow a more detailed analysis of competition's effect on the nonlinear pricing plans available to different customer types, allowing a welfare assessment of the effect of plan variety.

Appendix

Adoption Model

In this Appendix, we derive conditions that determine an incumbent's technology adoption decision in the face of entry by *n* competitors who have pre-committed to adopting the new technology. We tailor a subgame of the Fudenberg and Tirole (1986) model to our empirical setting where each incumbent faces several entrants and where we observe only whether the incumbents adopt the digital technology by 1998, the time of the initial PCS entry.[22] We thus analyze whether an incumbent chooses to adopt at a time t_1, before the entrants' pre-committed adoption time t_2, or to adopt only after entry at a time t_3, continuing to use using the pre-existing technology in the meantime.

If the incumbent adopts at time *t* before entry, the net present value of its future profits is:

$$V_1 = \int_0^t \Pi_0^I e^{-rx} dx + \int_t^{t_2} \Pi_1^I e^{-rx} dx + \int_{t_2}^{\infty} \Pi_1^E e^{-rx} dx - f(t) e^{-rt} \, , \tag{A1}$$

where Π_0^I denotes the incumbent's flow profits on the old technology before entry, Π_1^I the incumbent's flow profits on the new technology before entry, and Π_1^E the incumbent's flow profits on the new technology after entry. As in Fudenberg and Tirole (1986), we assume that $\Pi_0^I < \Pi_1^I$. $f(t)$ denotes the one-time cost of adopting the technology, which is decreasing and convex in the adoption time. The optimal time of adoption, t_1, occurs when:

$$t_1 = \min\left(t_2, t : -\left(\Pi_1^I - \Pi_0^I\right) e^{-rt} - \frac{d\left[f\left(t\right) e^{-rt} \right]}{dt} = 0 \right). \tag{A2}$$

If, on the other hand, the incumbent adopts after entry occurs, the net present value of its future profits is:

---

[22] As in Fudenberg and Tirole (1986), we derive the equilibrium for a single incumbent to simplify the exposition. We can extend their setup to two incumbents and *n* pre-committed entrants, allowing the incumbents to pre-empt each other strategically in their adoption timing of a cost-reducing innovation. We have chosen not to do so in this Appendix to focus attention on the incumbents' reaction to entry.

$$V_3 = \int_0^{t_2} \Pi_0^I e^{-rx} dx + \int_{t_2}^{t} \Pi_0^E e^{-rx} dx + \int_t^{\infty} \Pi_1^E e^{-rx} dx - f(t)e^{-rt}, \quad \text{(A3)}$$

where Π_0^E is the incumbent's flow profits on the old technology after entry and we assume that $\Pi_0^E < \Pi_1^E$. t_3 is determined by:

$$t_3 = \max\left(t_2, t: -\left(\Pi_1^E - \Pi_0^E\right)e^{-rt} - \frac{d\left[f(t)e^{-rt}\right]}{dt} = 0 \right). \quad \text{(A4)}$$

Simplifying, we get:

$$V_1 = \frac{1-e^{-rt_1}}{r}\Pi_0^I + \frac{e^{-rt_1} - e^{-rt_2}}{r}\Pi_1^I + \frac{e^{-rt_2}}{r}\Pi_1^E - f(t_1)e^{-rt_1}, \text{ and}$$
$$V_3 = \frac{1-e^{-rt_2}}{r}\Pi_0^I + \frac{e^{-rt_2} - e^{-rt_3}}{r}\Pi_0^E + \frac{e^{-rt_3}}{r}\Pi_1^E - f(t_3)e^{-rt_3}. \quad \text{(A5)}$$

The incumbent adopts prior to entry when $V_1 - V_3 > 0$. We can now determine how the number of entrants, *n*, affects the incumbent's adoption decision. The number of entrants affects only the incumbent's flow profits after entry, Π_0^E and Π_1^E. In turn, t_3 adjusts according to Equation (A4). Changes in the number of entrants alter whether the incumbent adopts before or after the entrants depending on the sign of:

$$\frac{d\left(V_1 - V_3\right)}{dn} = \left(\frac{e^{-rt_2} - e^{-rt_3}}{r}\right)\frac{d\left(\Pi_1^E - \Pi_0^E\right)}{dn}.[23] \quad \text{(A6)}$$

Therefore, if the incremental flow profits from adopting subsequent to entry increase in the number of entrants, $d\left(\Pi_1^E - \Pi_0^E\right)/dn > 0$, then additional entry makes it (weakly) more likely that the incumbent adopts prior to entry. We can now apply this to our empirical setting.

Up to this point, we have been agnostic about the form of the innovation or the form of competition between firms, as are Fudenberg and Tirole (1986). To derive more specific results about the adoption timing, we assume that the digital technology is a product innovation, specifically a vertical innovation relative to analog service, as discussed in

[23] Note that the remaining terms in the derivative of (V_1– V_3) with respect to *n* equal zero since the incumbent chooses its post-entry adoption timing optimally.

Section 3. Fudenberg and Tirole (1986) assume in contrast that the innovation is cost-reducing; however, to the extent that digital technology reduces the cost of providing service through better capacity management, such cost reductions are largely unaffected by the number of competitors. The cellular providers can be regarded as differentiated Bertrand competitors. Let $p_0^E(n)$ be the price of the incumbent's old-technology service and $p_1^E(n)$ be the incumbent's price of new-technology service. The incumbent's price for new-technology service declines directly with the number of rivals and for old-technology service indirectly since digital service is a substitute for analog service, so that $dp_0^E/dn, dp_1^E/dn < 0$.

In the absence of capacity constraints, the marginal cost of providing an additional minute of service on either technology is approximately zero and neither marginal nor fixed cost varies with the number of entrants. Let $q_0^E\left(p_0^E(n), p_1^E(n), n\right)$ and $q_1^E\left(p_1^E(n), n\right)$ denote the incumbent's demand for usage on the old and new technologies, respectively.[24] Then we can decompose the effect of entry on incremental flow profits as:

$$\frac{d\left(\Pi_1^E - \Pi_0^E\right)}{dn} = \frac{dp_1^E}{dn} q_1^E + p_1^E \left(\frac{\partial q_1^E}{\partial p_1^E} \frac{dp_1^E}{dn} + \frac{\partial q_1^E}{\partial n} \right) - \frac{dp_0^E}{dn} q_0^E - p_0^E \left[\frac{\partial q_0^E}{\partial p_1^E} \frac{dp_1^E}{dn} + \frac{\partial q_0^E}{\partial n} + \frac{\partial q_0^E}{\partial p_0^E} \frac{dp_0^E}{dn} \right]. \tag{A7}$$

This expression simplifies to:

$$\frac{d\left(\Pi_1^E - \Pi_0^E\right)}{dn} = \frac{dp_1^E}{dn} \left(1 + \varepsilon_1^E - \frac{\mathrm{Rev}_0^E}{\mathrm{Rev}_1^E} \varepsilon_{01}^E \right) q_1^E - \frac{dp_0^E}{dn} \left(1 + \varepsilon_0^E \right) q_0^E + \left(p_1^E \frac{\partial q_1^E}{\partial n} - p_0^E \frac{\partial q_0^E}{\partial n} \right), \tag{A8}$$

[24] If the incumbent adopts the digital technology, consumers cannot substitute to the analog technology.

where ε_0^E is the elasticity of the incumbent's demand for old-technology service, ε_1^E the elasticity of the incumbent's demand for new-technology service, ε_{01}^E the cross-price elasticity of demand between the two services, Rev_0^E the incumbent's revenue from old-technology service, and Rev_1^E the incumbent's revenue from new-technology service.

Therefore, the incumbent is (weakly) more likely to adopt prior to entry when its post-entry demand for new-technology service exceeds or is more elastic than the demand for old-technology service. Adoption occurs (weakly) earlier when the price for new-technology service is more sensitive to the number of entrants than the price for old-technology service or the demand for the old-technology service is more sensitive to the number of entrants than demand for the new-technology service. Finally, the incumbent is (weakly) more likely to adopt prior to entry when its revenues from new-technology service exceed those from old-technology service and the two services are not close substitutes.

In our setting, there are several reasons why post-entry profits under the old technology are likely more adversely affected by entry than those under the new technology. As discussed in Section 3 of the paper, the subscribers to digital technology service quickly overtook those to analog service, suggesting that post-entry demand for digital service was greater in magnitude than that for analog service and that analog-service demand declined significantly in the presence of even a few entrants. The elasticity of the incumbents' residual digital demand is likely greater than the elasticity for its residual analog demand since it faces more competition (on average 2.16 entrants versus at most one incumbent). Lastly, the price of digital service is undoubtedly more sensitive to the number of entrants than the price of analog service since all entrants offered digital service.

Estimation Procedure

Our system-of-equation results rely on full information maximum likelihood estimators that maximize the likelihood:

$$L = \prod_{m=1}^{M} \prod_{i=1}^{I} \prod_{t=A,D} L_{imt} \ . \tag{A9}$$

In estimating the system of equations with the number of plan introductions as our dependent variable, the likelihood of firm *i*'s observed behavior in market *m* and for plan technology *t* is:

$$\begin{aligned} L_{imt} &= \prod_{j=0}^{4} \prod_{k=0}^{1} \prod_{l=-6}^{9} \left[\Pr\left(Entrants_m = j, Digital_{im} = k, \Delta Plans_{imt} = l \right) \right]^{I_{jkl}} \\ I_{jkl} &= I\left(Entrants_m = j, Digital_{im} = k, \Delta Plans_{imt} = l \right) \end{aligned} \ . \tag{A10}$$

L_{imt} is given by the integral of the trivariate normal distribution of η_{im}^{D}, η_{m}^{E}, and η_{imt}^{P} with mean zero and variance-covariance matrix

$$\Sigma = \begin{bmatrix} 1 & \sigma_{DE} & \sigma_{DP} \\ \sigma_{DE} & 1 & \sigma_{EP} \\ \sigma_{DP} & \sigma_{EP} & 1 \end{bmatrix}, \tag{A11}$$

over the three-dimensional surface defined by f^{D}, f^{E}, f^{P} and the cutoffs C_1^E through C_4^E and C_{-5}^P through C_9^P consistent with the observed technology, number of entrants, and change in plans offered, respectively. The correlation between the errors in (A11) allows for correlation in the unobservables and therefore for endogeneity.

We use simulated maximum likelihood to maximize (A9). Beginning with a guess at the parameters of interest $\left\{ \alpha^{D}, \beta^{D}, \alpha^{E}, \beta^{E}, \alpha^{P}, \beta^{P} \right\}$ and the nuisance parameters $\left\{ \sigma_{DE}, \sigma_{DP}, \sigma_{EP}, C_1^E, ..., C_4^E, C_{-5}^P, ..., C_9^P \right\}$, we compute the likelihood using a Fortran routine for calculating trivariate normal probabilities developed in Genz (2004). We then use a numerical maximization routine to update the parameters until convergence.

For the remaining continuous plan variety measures, the likelihood of firm *i*'s observed behavior in market *m* and for plan technology *t* is:

$$
\begin{aligned}
L_{imt} &= \prod_{j=0}^{4}\prod_{k=0}^{1}\left[\Pr\left(Entrants_m = j, Digital_{im} = k, Variety_{imt} = v\right)\right]^{I_{jk}} \\
&= \prod_{j=0}^{4}\prod_{k=0}^{1}\left[\Pr\left(Entrants_m = j, Digital_{im} = k \left| Variety_{imt} = v\right.\right)\Pr\left(Variety_{imt} = v\right)\right]^{I_{jk}} \quad \text{(A12)} \\
I_{jk} &= I\left(Entrants_m = j, Digital_{im} = k\right)
\end{aligned}
$$

where the variance-covariance matrix of η_{im}^{D}, η_{m}^{E}, and η_{imt}^{P} is now given by

$$
\Sigma = \begin{bmatrix} 1 & \sigma_{DE} & \sigma_{DP} \\ \sigma_{DE} & 1 & \sigma_{EP} \\ \sigma_{DP} & \sigma_{EP} & \sigma_{P}^{2} \end{bmatrix}. \tag{A13}
$$

The probability of observing $Variety_{imt} = v$ equals $\phi\left((v - f^{P})\sigma_{P}^{-1}\right)$, where $\phi(\cdot)$ denotes the standard normal pdf, while the probability of the entry and adoption behavior is given by the integral of the bivariate normal distribution of η_{im}^{D} and η_{m}^{E}, conditional on $Variety_{imt} = v$, with mean and variance-covariance matrix:

$$
\mu = \begin{bmatrix} v\dfrac{\sigma_{DP}}{\sigma_{P}^{2}} \\ v\dfrac{\sigma_{EP}}{\sigma_{P}^{2}} \end{bmatrix} \quad \text{and} \quad \Sigma = \begin{bmatrix} 1-\left(\dfrac{\sigma_{DP}}{\sigma_{P}}\right)^{2} & \sigma_{DE} - \left(\dfrac{\sigma_{DP}\sigma_{EP}}{\sigma_{P}^{2}}\right) \\ \sigma_{DE} - \left(\dfrac{\sigma_{DP}\sigma_{EP}}{\sigma_{P}^{2}}\right) & 1-\left(\dfrac{\sigma_{EP}}{\sigma_{P}}\right)^{2} \end{bmatrix}, \tag{A14}
$$

over the surface defined by f^{D}, f^{E}, and the cutoffs C_{1}^{E} through C_{4}^{E} consistent with the observed technology and number of entrants.

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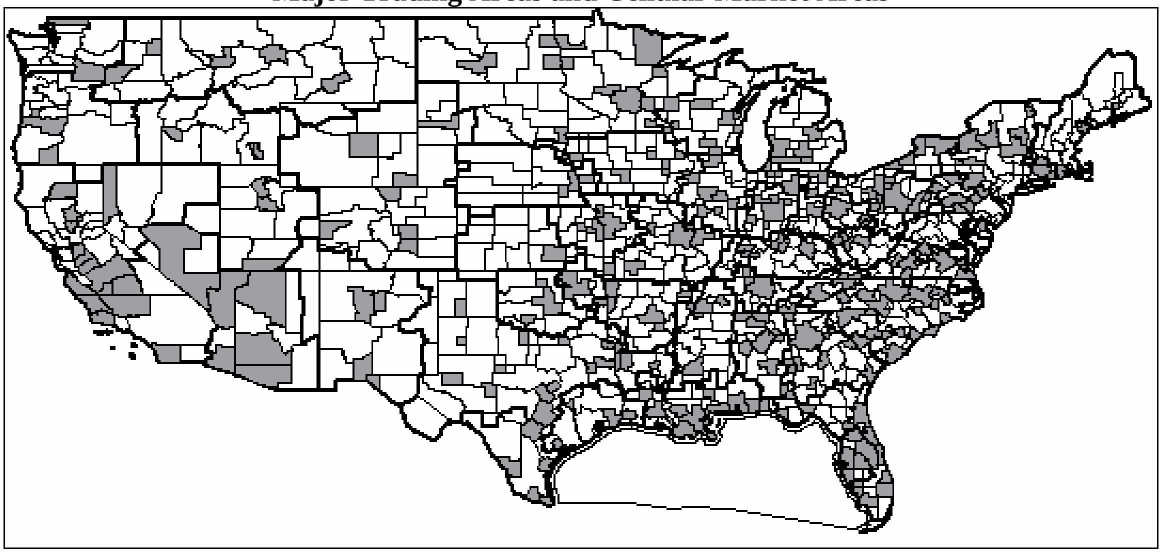
Figures and Tables

Figure 1
Major Trading Areas and Cellular Market Areas



This map shows the geographic market areas for cellular service. The dark bordered regions are the 51 MTAs and the light-bordered areas are the CMAs. Shaded CMAs denote the set of 100 largest cellular markets in 1996.

Table 1
Entrants' Activation of Systems by Launch Quarter, 100 Largest Cellular Markets
Fourth Quarter 1995 – Second Quarter 1998

Quarter of Launch	Number of Launches	Average Build-Out Time (Months)	Average Market Size
Q4-1995	2	11.0	3,538,229
Q1-1996	-	-	-
Q2-1996	2	13.0	1,062,081
Q3-1996	13	16.6	1,553,067
Q4-1996	39	20.2	2,031,327
Q1-1997	35	23.4	1,884,427
Q2-1997	28	26.0	2,205,694
Q3-1997	31	28.2	2,269,856
Q4-1997	34	30.0	1,746,194
Q1-1998	12	33.1	2,062,024
Q2-1998	22	26.8	1,900,680
Total	218	25.3	1,951,804

Source: *PCS Week* , various issues. Companies' public filings.
Note: Average build-out times are computed for PCS entrants only as the delay between license award and system activitation.

Table 2
Descriptive Statistics, 98 Largest Cellular Markets

Variable	Observations	Mean	Standard Deviation	Min	Max
Incumbents' Plan Family Characteristics					
Number of Plans per Analog Plan Family, 1996	193	5.89	1.30	3.00	8.00
Change in the Number of Plans Offered, 1996-98	193	2.80	3.47	-5.00	12.00
Analog Plan Families, if offered	178	-0.07	1.92	-6.00	5.00
Digital Plan Families, if offered	128	5.06	1.58	2.00	9.00
Percent of Analog Plan Families, 1998	306	0.58	0.49	0.00	1.00
Analog Plan Characteristics, 1998					
Fixed Fee	1,017	72.06	64.87	9.95	592.99
Included Number of Peak Minutes	1,017	301.05	470.98	0.00	3,560.00
Incumbents' Digital Plan Characteristics, 1998					
Fixed Fee	713	73.24	47.96	14.95	279.99
Included Number of Peak Minutes	713	555.74	558.04	0.00	3,000.00
Incumbents' Technology Choice by Market, 1998					
Percent of Analog Only Providers[1]	193	0.34	0.47	0.00	1.00
Percent of Digital Only Providers[1]	193	0.08	0.27	0.00	1.00
Percent of Mixed Technology Providers[1]	193	0.59	0.49	0.00	1.00
Incumbent Characteristics					
Number of Markets Present	24	12.75	15.59	1.00	48.00
Percent of Providers with Small Potential Network	24	0.63	0.49	0.00	1.00
Percent of Providers with Large Potential Network	24	0.21	0.41	0.00	1.00
Market Characteristics					
Entrants per Market	98	2.16	1.08	0.00	4.00
Zero Entrants	98	0.05	0.22	0.00	1.00
One Entrant	98	0.26	0.44	0.00	1.00
Two Entrants	98	0.28	0.45	0.00	1.00
Three Entrants	98	0.32	0.47	0.00	1.00
Four Entrants	98	0.10	0.30	0.00	1.00
Population (000)	98	1,524.66	1,662.93	175.20	9,519.34
Average Commuting Time (mins)	98	24.58	3.25	19.00	38.90
Household Income (000)	98	44.03	7.18	31.05	74.34
Percent with B.A. or more	98	24.41	5.43	13.09	41.66
Heterogeneity in Commuting Time	98	87.57	1.06	84.58	89.98
Heterogeneity in Income	98	92.46	0.23	91.68	93.09
Heterogeneity in Education	98	83.97	1.82	77.14	86.80

Notes:
[1] The unit of observation is the market and provider, measuring the percent of providers that offer a given technology in the market, but not whether the provider offers analog, digital, or both technologies on its entire network across markets.

Table 3
Variable Description and Data Sources

Variable	Description	Data Source
Chg_Plans	Change in the number of plans offered by cellular incumbents in each market within a given technology.	Kagan World Media
Plan-Family Herfindahl[1]	Herfindahl index based on share of minutes allocated to each calling plan.	
Share of High-Usage Plans	Number of calling plans with an allowance greater than 180 minutes as a share of the number of plans in the family.	
Prov_Analog	Indicator variable: Provider offers analog service only in both 1996 and 1998.	
Prov_Mixed	Indicator variable: Provider offers separate analog and digital plan choices in 1998.	
Prov_Digital	Indicator variable: Provider offers digital service only in 1998.	
Plans_Analog	Indicator variable: Plan family's technology is analog.	
Plans_Digital	Indicator variable: Plan family's technology is digital.	
Entrants	Number of entrants into the market between 1996 and 1998.	
Large Geographic Scope	Indicator variable: Provider offers cellular service in more than 15 of the top 100 cellular markets.	
Small Geographic Scope	Indicator variable: Provider offers cellular service in at most 5 of the top 100 cellular markets.	
Population	MSA population in thousands.	Census 2000
Area	MSA area in square miles.	
% City	Share of the MSA's area contained in its central cities.	
Commuting Time	Average commuting time in minutes.	
Household Income	Household income in thousands of dollars.	
% with B.A. or more	Percent of the MSA population with at least a B.A. degree.	
Heterogeneity in Communting Time[2]	Heterogeneity index. Groups classify shares of workers with commuting time. Categories begin at 5, 10, 15, 20, 25, 30, 35, 40, 45, 60, and 90 minutes.	
Heterogeneity in Household Income[2]	Heterogeneity index. Groups classify shares of households with income in thousands. Categories begin at \$10, \$15, \$20, \$25, \$30, \$35, \$40, \$45, \$50, \$60, \$75, \$100, \$125, \$150, and \$200.	
Heterogeneity in Educational Attainment[2]	Heterogeneity index. Groups classify shares of population 25 years and older. Categories are less than a 9th grade education; 9th-12th grade education; high school graduate or higher, no B.A.; B.A. or higher.	
Elev-Avg	Average elevation using elevation at regular gird points in the MSA.	US Geological Survey
Elev-SD	Standard deviation in elevation at regular grid points in the MSA.	

[1] The Herfindahl index is defined as:

$$\text{Herfindahl Index} = \sum_{j=1}^{J}\left(\frac{\bar{q}_j - \bar{q}_{j-1}}{\bar{q}_J}\right)^2 \text{ where } \bar{q}_j \text{ denotes the allowance on tariff } j \text{ and } \bar{q}_0 = 0 < \bar{q}_1 < \ldots < \bar{q}_J .$$

[2] The heterogeneity index for commuting time, household income and educational attainment is defined as:

$$\text{Heterogeneity Index} = 1 - \sum_i (share\ of\ group_i)^2$$

Table 4
Change in Number of Plans, 1996-1998, and Digital Technology Adoption, Cellular Incumbents, Linear Models

	OLS		2SLS	
	Adoption	Plan Change	Adoption	Plan Change
Technologies offered by Provider in 1998				
Prov_Analog		-1.4216		-0.6230
		(1.0966)		(1.6220)
Prov_Mixed		0.1127		-0.1156
		(1.0201)		(1.1377)
Plans' Type of Technology				
Plans_Digital		3.0159 ***		3.1026 ***
		(0.3615)		(0.6672)
Market Characteristics				
Prov_Analog*Entrants		0.4983 **		-0.2439
		(0.2218)		(0.4556)
Prov_Digital*Entrants		0.2678		-0.0517
		(0.4285)		(0.5037)
Prov_Mix.*Plans_An.*Entrants		-0.4416 **		-0.5890 **
		(0.2001)		(0.2618)
Prov_Mix.*Plans_Dig.*Entrants		0.4844 ***		0.3294 *
		(0.0829)		(0.1974)
Entrants	0.0959 *		0.2104 ***	
	(0.0522)		(0.0634)	
% with B.A. or more	-0.0081		-0.0089	
	(0.0097)		(0.0095)	
Commuting Time	0.0055		0.0104	
	(0.0162)		(0.0157)	
Population	0.0039 **	0.0036	-0.0002	0.0043
	(0.0017)	(0.0098)	(0.0022)	(0.0099)
Household Income	0.0108 **		0.0070	
	(0.0053)		(0.0058)	
Provider Characteristics				
Large Geographic Scope	0.1901 ***		0.1400 ***	
	(0.0368)		(0.0346)	
Small Geographic Scope	-0.2634 **		-0.3215 ***	
	(0.1038)		(0.0758)	
Demand Heterogeneity Measures				
Het. in Commuting Time		-0.1038		-0.0143
		(0.1643)		(0.1756)
Het. in Household Income		-0.7202 **		-0.5285
		(0.3231)		(0.3334)
Het. in Educational Attainment		-0.0148		0.0447
		(0.0676)		(0.0699)
Adj. R-Squared	0.3877	0.7392	0.3925	0.7289
Observations	193	306	193	306

Selected provider fixed effects included in plan change and digital adoption decision equations. Standard errors in parentheses are clustered at the provider level and are based on 100 bootstrapped samples for the nonlinear IV estimates. * = 10% significance, ** = 5% significance, *** = 1% significance. The estimated coefficients of the entry equation with the corresponding standard errors in parentheses are for the 2SLS specification:

$$ENTRANTS = \underset{(0.0185)}{0.0999}\,POP - \underset{(0.0002)}{0.0009}\,POP^2 + \underset{(0.0864)}{0.0981}\,AREA - \underset{(0.0022)}{0.0021}\,AREA^2 + \underset{(0.9120)}{0.4299}\,\%CITY - \underset{(0.2939)}{0.1700}\,ELEV\text{-}AVG - \underset{(1.1133)}{0.4301}\,ELEV\text{-}SD + \varepsilon,$$

for the nonlinear plan change IV specification:

$$ENTRANTS = \underset{(0.0106)}{0.1462}\,POP - \underset{(0.0001)}{0.0013}\,POP^2 + \underset{(0.0368)}{0.1908}\,AREA - \underset{(0.0009)}{0.0043}\,AREA^2 + \underset{(0.2944)}{1.0254}\,\%CITY - \underset{(0.3621)}{0.9432}\,ELEV\text{-}AVG - \underset{(0.1753)}{0.2087}\,ELEV\text{-}SD + \varepsilon,$$

where POP denotes the 1999 CMA population, AREA the CMA's landarea, %CITY the percentage of the area that falls within the central cities of the CMA, and ELEV-AVG and ELEV-SD the average and standard deviation of the CMA's elevation. The entrant equation also includes six region indicators.

Table 5
Change in Number of Plans, 1996-1998, and Digital Technology Adoption, Cellular Incumbents, Nonlinear IV

	Single-Equation FIML Estimation						System-of-Equations FIML Estimation		
	Coefficient	Std. Error	Marg. Effect	Coefficient	Std. Error	Marg. Effect	Coefficient	Std. Error	Marg. Effect
Plan Change Equation									
Prov_Analog	-0.8672 ***	0.2192	-1.2826				-0.9645 ***	0.2974	-1.4227
Prov_Mixed	-0.1902	0.2254	-0.2813				-0.0736	0.2489	-0.1086
Plans' Type of Technology									
Plans_Digital	2.1032 ***	0.1536	3.1105				2.1080 ***	0.1807	3.1096
Entry by PCS Providers									
Prov_Analog*Entrants	0.1315	0.1163	0.1945				0.1427	0.1294	0.2106
Prov_Digital*Entrants	-0.0628	0.1165	-0.0929				0.0228	0.1273	0.0337
Prov_Mixed* (Plans_Analog)*Entrants	-0.3048 ***	0.0843	-0.4507				-0.3025 ***	0.0901	-0.4463
Prov_Mixed* (Plans_Digital)*Entrants	0.2979 ***	0.0628	0.4406				0.2944 ***	0.0587	0.4343
Population	0.0013	0.0027	0.0020				-0.0002	0.0029	-0.0003
Demand Heterogeneity									
Commuting Time Index	-0.0514 ***	0.0031	-0.0759				-0.0498 ***	0.0031	-0.0735
Household Income Index	-0.4657 ***	0.0027	-0.6888				-0.4684 ***	0.0036	-0.6909
Edu. Attainment Index	-0.0002	0.0026	-0.0002				0.0007	0.0042	0.0010
Digital Adoption Decision Equation									
Entrants				0.7715 ***	0.2008	0.2287	0.5048 **	0.2198	0.0977
Percent with B.A. or more				-0.0363 *	0.0187	-0.0108	-0.0437 ***	0.0154	-0.0085
Commuting Time				0.0059	0.0242	0.0018	0.0192	0.0255	0.0037
Population				0.0067	0.0128	0.0020	0.0272 *	0.0206	0.0053
Household Income				0.0277 *	0.0142	0.0082	0.0367 ***	0.0105	0.0071
Large Geographic Scope				1.9650 ***	0.2176	0.5824	2.2503 ***	0.2191	0.4356
Small Geographic Scope				1.5678 ***	0.2612	0.4647	1.6390 ***	0.2418	0.3172
Log-Likelihood	-879.83			-280.30			-986.22		
Observations	306			193			306		

Selected provider fixed effects included in plan change and digital adoption decision equations. Provider-level clustered standard errors based on 100 bootstrapped samples in parentheses. * = 10% significance, ** = 5% significance, *** = 1% significance. The estimated coefficients of the entry equation with the corresponding bootstrap standard errors in parentheses are for the single-equation plan-change specification:

$$ENTRANTS = \underset{(0.0106)}{0.1462}\,POP - \underset{(0.0001)}{0.0013}\,POP^2 + \underset{(0.0368)}{0.1908}\,AREA - \underset{(0.0009)}{0.0043}\,AREA^2 + \underset{(0.2944)}{1.0254}\,\%CITY - \underset{(0.3621)}{0.9432}\,ELEV\text{-}AVG - \underset{(0.1753)}{0.2087}\,ELEV\text{-}SD + \eta^E,$$

with estimated correlation coefficient ρ=-0.27; for the single-equation adoption specification:

$$ENTRANTS = \underset{(0.0109)}{0.1612}\,POP - \underset{(0.0001)}{0.0014}\,POP^2 + \underset{(0.0363)}{0.1143}\,AREA - \underset{(0.0012)}{0.0024}\,AREA^2 + \underset{(0.5655)}{0.4122}\,\%CITY - \underset{(0.4442)}{1.0166}\,ELEV\text{-}AVG - \underset{(0.1427)}{0.1014}\,ELEV\text{-}SD + \eta^E,$$

with estimated correlation coefficient ρ = -0.62; and for the system-of-equations specification:

$$ENTRANTS = \underset{(0.0134)}{0.1516}\,POP - \underset{(0.0001)}{0.0014}\,POP^2 + \underset{(0.0390)}{0.1769}\,AREA - \underset{(0.0010)}{0.0038}\,AREA^2 + \underset{(0.4678)}{1.0144}\,\%CITY - \underset{(0.1693)}{0.2756}\,ELEV\text{-}AVG - \underset{(0.3951)}{0.8301}\,ELEV\text{-}SD + \eta^E.$$

with estimated correlation coefficients {ρ12,ρ13,ρ23} = {0.09,-0.12,-0.28}. The variables in the entrant equation are defined in the footnote to Table 4.

Table 6
Summary Statistics, Allowance-Based Plan Placement Measures, Incumbents' and Entrants' 1998 Plans

	Mean	Std. Dev.	Min	Max	Obs.
Full Menu of Plans					
Herfindahl, Plan Families with 5 - 7 Plans	0.358	0.108	0.193	0.789	335
Normalized Herfindahl, All Plan Families	1.936	0.708	1.000	5.868	506
"High-Usage" Plans					
Share of Plans Above Median, All Plan Families	0.553	0.214	0.000	1.000	521
Herfindahl Above Median, Plan Families with 5 - 7 Plans	0.468	0.182	0.208	1.000	335
Normalized Herfindahl Above Median, All Plan Families	1.325	0.390	1.000	3.021	504

Table 7
Placement of Incumbents' and Entrants' 1998 Pricing Plans: FIML Estimation

	Normalized Herfindahl based on Allowance Levels, All 1998 Plan Families		Herfindahl based on Allowance Levels, 1998 Plan Families with 5-7 Plans	
	Coefficient	Standard Error	Coefficient	Standard Error
Providers' Type of Technology				
Prov_Analog	-0.3547 ***	0.1042	0.0605	0.1996
Prov_Mixed	-0.7669 ***	0.1264	-0.1437 *	0.0902
Entrant	0.4296 ***	0.1110	0.0449	0.0730
Plans' Type of Technology				
Plans_Digital	-1.2042 ***	0.1080	-0.0341	0.0573
Market Structure				
Prov_Analog*Competitors	-0.2457 ***	0.0432	-0.0574 **	0.0325
Prov_Digital*Competitors	-0.1485 ***	0.0399	-0.0309 *	0.0222
Prov_Mixed* (Plans_Analog)*Competitors	-0.1240 ***	0.0365	-0.0061	0.0189
Prov_Mixed* (Plans_Digital)*Competitors	0.0583 *	0.0396	-0.0072	0.0133
Demand Characteristics				
Percent with B.A. or more	-0.0288 ***	0.0091	-0.0047 ***	0.0004
Commuting Time	-0.0086	0.0074	-0.0059 **	0.0027
Population	0.0031 **	0.0013	0.0009	0.0156
Household Income	-0.3176 ***	0.0094	-0.0499 ***	0.0031
Std. deviation, η^{Herf}	0.5732 ***	0.0358	0.0885	0.2901
Log-Likelihood	-1081.55		-58.89	
Observations	506		335	

Selected provider fixed effects included in curvature and digital adoption decision equations. Provider-level clustered standard errors based on 100 bootstrapped samples in parentheses. * = 10% significance, ** = 5% significance, *** = 1% significance. The estimated coefficients of the two auxiliary equations, with the corresponding bootstrap standard errors in parentheses, are for Specification I:

$$ENTRANTS = \underset{(0.0114)}{0.1458}\, POP - \underset{(0.0001)}{0.0013}\, POP^2 + \underset{(0.0395)}{0.1641}\, AREA - \underset{(0.0018)}{0.0036}\, AREA^2 + \underset{(0.1327)}{1.0866}\, \%CITY - \underset{(0.1506)}{0.9983}\, ELEV\text{-}AVG - \underset{(0.0917)}{0.1314}\, ELEV\text{-}SD + \eta^E$$

$$ADOPTION = \underset{(0.0951)}{0.5869}\, ENTRANTS - \underset{(0.0196)}{0.0340}\, BAPLUS + \underset{(0.0237)}{0.0274}\, COMMUTE + \underset{(0.0150)}{0.0206}\, POP + \underset{(0.0180)}{0.0313}\, INCOME$$
$$+ \underset{(0.0932)}{2.3255}\, LARGE\text{-}SC + \underset{(0.0935)}{1.77076}\, SMALL\text{-}SC + \eta^A$$

and for Specification II:

$$ENTRANTS = \underset{(0.1844)}{0.1517}\, POP - \underset{(0.0167)}{0.0014}\, POP^2 + \underset{(0.0002)}{0.0808}\, AREA - \underset{(0.0479)}{0.0017}\, AREA^2 + \underset{(0.0014)}{0.6053}\, \%CITY + \underset{(0.1875)}{0.0124}\, ELEV\text{-}AVG + \underset{(0.2661)}{0.0040}\, ELEV\text{-}SD + \eta^E$$

$$ADOPTION = \underset{(0.2901)}{0.7287}\, ENTRANTS - \underset{(0.2108)}{0.04148}\, BAPLUS + \underset{(0.0305)}{0.0117}\, COMMUTE + \underset{(0.0300)}{0.0129}\, POP + \underset{(0.0199)}{0.0314}\, INCOME$$
$$+ \underset{(0.1911)}{1.8362}\, LARGE\text{-}SC + \underset{(0.2179)}{1.1900}\, SMALL\text{-}SC + \eta^A$$

The variables in the entrant equation are defined in the footnote to Table 4. In the adoption euqation, ENTRANTS denotes the number of entrants, BAPLUS the percent of the MSA population with at least a B.A. degree, COMMUTE the average commuting time, POP the MSA population, INCOME its income, and LARGE-SC and SMALL-SC indicate whether the provider operates a large or small network, respectively. The estimated correlation coefficients {ρ12,ρ13,ρ23} are {0.01,0.11,-0.68} for Specification I and {0.03,0.32,-0.61} for Specification II.

Table 8
Placement of High-Usage Plans, Incumbents' and Entrants' 1998 Pricing Plans: FIML Estimation

	Share of Plans above Median		Normalized Herfindahl above Median		Herfindahl above Median, Plan Families with 5-7 Plans	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Providers' Type of Technology						
Prov_Analog	0.1533 *	0.1139	-0.0068	0.1054	0.1530	0.1251
Prov_Mixed	0.2124 **	0.0982	-0.1251	0.1309	-0.2623 **	0.1135
Entrant	-0.1799 ***	0.0682	-0.1492 *	0.0975	0.0661	0.0921
Plans' Type of Technology						
Plans_Digital	0.3831 ***	0.0859	-0.1769	0.1643	-0.1097 **	0.0526
Market Structure						
Prov_Analog*Competitors	0.0390 **	0.0193	-0.1482 ***	0.0394	-0.1138 ***	0.0313
Prov_Digital*Competitors	0.0610 **	0.0287	-0.0414 *	0.0303	-0.0700 ***	0.0253
Prov_Mixed* (Plans_Analog)*Competitors	0.0201 **	0.0120	-0.0923 ***	0.0294	-0.0118	0.0148
Prov_Mixed* (Plans_Digital)*Competitors	0.0098	0.0154	-0.0114	0.0471	-0.0234	0.0192
Demand Characteristics						
Percent with B.A. or more	0.0014	0.0014	0.0123 ***	0.0025	0.0004	0.0032
Commuting Time	0.0035	0.0031	-0.0007	0.0062	-0.0072 *	0.0049
Population	-0.0007 *	0.0005	-0.0004	0.0007	0.0019 **	0.0008
Household Income	-0.0052 ***	0.0009	-0.0095 ***	0.0026	0.0032 *	0.0023
Std. deviation, η^Y	0.1488 ***	0.0082	0.3270 ***	0.0219	0.1451 ***	0.0075
Log-Likelihood	-354.76		-760.51		-205.25	
Observations	521		504		335	

Selected provider fixed effects included in curvature and digital adoption decision equations. Provider-level clustered standard errors based on 100 bootstrapped samples in parentheses. * = 10% significance, ** = 5% significance, *** = 1% significance. The estimated coefficients of the entry equation with the corresponding bootstrap standard errors in parentheses are for Specification I:

$$ENTRANTS = \underset{(0.0103)}{0.1372}\,POP - \underset{(0.0001)}{0.0012}\,POP^2 + \underset{(0.0459)}{0.1832}\,AREA - \underset{(0.0028)}{0.0042}\,AREA^2 + \underset{(0.6417)}{0.6134}\,\%CITY - \underset{(0.5007)}{1.3324}\,ELEV\text{-}AVG - \underset{(0.1492)}{0.0032}\,ELEV\text{-}SD + \eta^E$$

$$ADOPTION = \underset{(0.2448)}{0.7167}\,ENTRANTS - \underset{(0.0211)}{0.0272}\,BAPLUS + \underset{(0.0408)}{0.0163}\,COMMUTE + \underset{(0.0147)}{0.0094}\,POP + \underset{(0.0170)}{0.0231}\,INCOME + \underset{(0.3815)}{1.9122}\,LARGE\text{-}SC + \underset{(0.4955)}{1.5813}\,SMALL\text{-}SC + \eta^A$$

for Specification II:

$$ENTRANTS = \underset{(0.0135)}{0.1466}\,POP - \underset{(0.0001)}{0.0013}\,POP^2 + \underset{(0.0513)}{0.1688}\,AREA - \underset{(0.0014)}{0.0038}\,AREA^2 + \underset{(0.6136)}{1.0382}\,\%CITY - \underset{(0.4788)}{1.1583}\,ELEV\text{-}AVG - \underset{(0.1929)}{0.0695}\,ELEV\text{-}SD + \eta^E$$

$$ADOPTION = \underset{(0.2078)}{0.7453}\,ENTRANTS - \underset{(0.0212)}{0.0306}\,BAPLUS + \underset{(0.0316)}{0.0053}\,COMMUTE + \underset{(0.0105)}{0.0099}\,POP + \underset{(0.0184)}{0.0233}\,INCOME + \underset{(0.3398)}{2.1446}\,LARGE\text{-}SC + \underset{(0.3625)}{1.4718}\,SMALL\text{-}SC + \eta^A$$

and for Specification III:

$$ENTRANTS = \underset{(0.0170)}{0.1219}\,POP - \underset{(0.0002)}{0.0010}\,POP^2 + \underset{(0.0518)}{0.1855}\,AREA - \underset{(0.0018)}{0.0044}\,AREA^2 - \underset{(0.2458)}{0.2382}\,\%CITY - \underset{(0.2970)}{1.7127}\,ELEV\text{-}AVG + \underset{(0.1827)}{0.3224}\,ELEV\text{-}SD + \eta^E$$

$$ADOPTION = \underset{(0.1983)}{0.1219}\,ENTRANTS - \underset{(0.2419)}{0.0010}\,BAPLUS + \underset{(0.2063)}{0.1855}\,COMMUTE - \underset{(0.2238)}{0.0044}\,POP - \underset{(0.2596)}{0.2382}\,INCOME + \underset{(0.2091)}{0.3224}\,LARGE\text{-}SC - \underset{(0.2011)}{1.7817}\,SMALL\text{-}SC + \eta^A$$

The variables are defined in the footnotes to tables 4 and 7. The estimates of the correlation coefficients {ρ12,ρ13,ρ23} are {0.01,0.11,-0.68} for Specification I, {0.11,-0.15,-0.59} for Specification II, and {0.26,-0.44,-1.73} for Specification III.

Table 9

Distribution of Estimated Curvature of Incumbents' and Entrants' 1998 Pricing Schedules

	Analog Plans, Incumbents	Digital Plans, Incumbents	Entrants
Mean	0.627	0.444	0.486
Std. Dev.	0.093	0.109	0.099
Min	0.402	0.167	0.197
Max	0.920	0.837	0.844
Percentiles:			
5%	0.465	0.260	0.282
25%	0.560	0.404	0.438
50%	0.640	0.432	0.483
75%	0.689	0.492	0.552
95%	0.774	0.653	0.616
Avg. Adj. R^2	0.946	0.872	0.903
Obs.	178	128	215

Table 10
Curvature of Incumbents' and Entrants' 1998 Pricing Schedules: FIML Estimation

	Coefficient	Standard Error
Providers' Type of Technology		
Prov_Analog	-0.0710	0.0561
Prov_Mixed	-0.1305 ***	0.0355
Entrant	0.0066	0.0453
Plans' Type of Technology		
Plans_Digital	-0.2388 ***	0.0388
Market Structure		
Prov_Analog*Competitors	-0.0390 ***	0.0110
Prov_Digital*Competitors	-0.0272 **	0.0108
Prov_Mixed*(Plans_Analog)*Competitors	-0.0102 *	0.0068
Prov_Mixed*(Plans_Digital)*Competitors	0.0006	0.0070
Demand Characteristics		
Percent with B.A. or more	-0.0019	0.0019
Commuting Time	0.0027	0.0021
Population	-0.0003	0.0003
Household Income	0.0024 **	0.0013
Std. deviation, η^{curv}	0.0889 ***	0.0049
Fixed Effects	Provider level	
Log-Likelihood	-106.84	
Observations	521	

* = 10% significance, ** = 5% significance, *** = 1% significance.
Standard errors for the IV-FIML estimation adjust for provider-level clustering based on 100 bootstrapped samples in parentheses. The estimates of the correlation coefficients {ρ12,ρ13,ρ23} are {0.23,-0.17,-0.07}. The estimated coefficients of the two auxiliary equations, with corresponding bootstrapped standard errors in parentheses are:

$$ENTRANTS = \underset{(0.0129)}{0.1392}\,POP - \underset{(0.0001)}{0.0013}\,POP^2 + \underset{(0.0431)}{0.2019}\,AREA - \underset{(0.0014)}{0.0046}\,AREA^2 + \underset{(0.1844)}{0.7962}\,\%CITY$$
$$-\underset{(0.1623)}{1.1054}\,ELEV\text{-}AVG - \underset{(0.1228)}{0.0958}\,ELEV\text{-}SD + \eta^E$$

$$ADOPTION = \underset{(0.1091)}{0.2823}\,ENTRANTS - \underset{(0.0202)}{0.0350}\,BAPLUS + \underset{(0.0218)}{0.0346}\,COMMUTE - \underset{(0.0157)}{0.0430}\,POP$$
$$+\underset{(0.0167)}{0.0374}\,INCOME + \underset{(0.1156)}{2.2325}\,LARGE\text{-}SC + \underset{(0.1074)}{1.7817}\,SMALL\text{-}SC + \eta^A$$

The variables are defined in the footnotes to tables 4 and 7.