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

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March 4, 2010

Abstract

We examine how structural changes in the cellular services industry between 1996, when local markets were duopolies, and 1998, when they had experienced varying degrees of regulated entry, simultaneously affected firms' product offerings and nonlinear pricing strategies. We relate digital technology adoption and the characteristics of calling plan menus to the amount of entry in different local markets. To control for potential endogeneity between entry decisions and firms' technology and pricing decisions, we employ variation in geographic features of the markets as an instrument. We find that entry causes an increase in the number of plans offered, both as a direct result of competition, and as an indirect result of the introduction of digital service that is marketed with more plan offerings. In markets with more entry, incumbents and entrants spread plans more evenly over the usage spectrum and are more likely to lower prices. However, high-valuation consumers benefit more than low-valuation consumers as firms offer more high-usage plans and offer steeper quantity discounts in markets with more entry. Our results have implications for regulators who seek to promote the availability of newer technologies to a heterogeneous consumer market by influencing market structure.

Keywords: entry, market structure, technology adoption, price discrimination, nonlinear pricing, telecommunications
JEL Codes: L11, L13, L25, L96

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* We would like to thank Michael Grubb, John Johnson, and Li Xing for excellent research assistance, Anja Lambrecht, Philip Leslie, John Parapatt, and Catherine Tucker for helpful comments, and Dan Ackerberg for providing us with computer code for a related problem. This research was supported by the NET Institute and the Stanford Center for Electronic Business and Commerce.
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1. Introduction

Wireless carriers offered on average 5.9 different calling plans in a market in 1996. By 2002, that number had increased to 17.5 before falling to 3.7 by 2007.[1] In part, these changes reflect the introduction, and later elimination, of vertically differentiated services, such as different transmission technologies and sizes of calling areas. They also reflect adjustments in the carriers' use of second-degree price discrimination in response to factors such as increasing demand heterogeneity, increased availability of wireless spectrum, and changes in market structure.

Only a few theoretical results and limited empirical research are available to inform how market structure affects firms' second-degree price discrimination strategies and consequent welfare effects. Even less is known about market structure's simultaneous impact on firms' product offerings and use of price discrimination. This interaction has important welfare consequences in many empirical settings, particularly communications and information industries, such as wireless communications, Internet access, and content distribution. These industries experience (1) frequent market structure changes through reorganizations or new entry, (2) frequent product innovations due to technological change, and (3) price discrimination based on menus of nonlinear price schedules.

In this paper, we assess the impact of market structure on firms' price discrimination strategies, both directly, through competitive interaction, and indirectly, through its influence on how quickly firms market new services and discontinue old ones. We employ comprehensive, geographically detailed data on nonlinear pricing plans offered by wireless carriers in 1996 and in 1998. Between the two years, personal communication services (PCS) providers entered wireless duopoly markets and incumbents began introducing digital service that improved on the existing analog service in call features and spectrum management. In our setting we can assess the relative importance of the direct effect of competition and the indirect effect, via technology adoption, of market structure on pricing. We find that the typical range of indirect effects is from 15.5 percent

[1] Authors' calculations based on data from Kagan World Media and MyRatePlan.com, LLC.

to 94.4 percent of the overall effects of market structure, depending on the outcome variable, reflecting that carriers provide both more plan variety and greater price decreases for the new than for the old technology. We find that indirect effects are less significant in affecting the spacing of plans along the usage spectrum.

Theoretical work on the direct effect of competition (including Stole 1995, Spulber 1989, Gal-Or 1988, and Oren, Smith, and Wilson 1983) focuses on the relationship between the number of firms and the breadth and curvature of nonlinear price schedules. A common finding is that greater competition leads firms to lower their price schedules toward marginal cost, increases consumer participation in the market, and reduces welfare distortions between high- and low-valuation consumers. Johnson and Myatt (2003, 2006) and Yang and Ye (2008) consider the effect of changes in market structure when firms are horizontally differentiated. The latter authors show that when high-valuation consumers' vertical preferences are sufficiently strong to overwhelm horizontal differences, firms compete directly for those consumers. This competition results in finer price discrimination and greater price decreases for high- than for low-valuation types as the number of firms increases. These theoretical results are consistent with our findings on the overall effect of entry and the differential effects by consumer type.

Theoretical work relevant to the indirect effect of market structure via new product pricing focuses on the strategic determinants of product diffusion speed, specifically the possibility that a firm would adopt a product preemptively to deter or delay adoption by other firms. Reinganum (1981a, b) points to two offsetting effects: lower firm concentration increases the competitive pressure on an individual firm to gain a relative advantage early, but it also drives down post-adoption profits, inducing firms to wait for the costs of adoption to go down. Fudenberg and Tirole (1985) imply that, when competition increases, technology adoption increases because there are more opportunities for firms to steal business. In aggregate, this literature yields inconclusive predictions for the effect of market structure on the speed of diffusion (see Hoppe 2002 for a more extensive review). However, we show in the Appendix that by tailoring a model to the regulated entry observed in our setting, theoretical predictions are consistent with our empirical finding that entry accelerates adoption when incumbents' profits fall more when they remain with an old technology than when they upgrade to a new, substitute technology. We argue that the latter condition is likely to hold in our setting as well as in communications and information industries more broadly.

Previous empirical results on the effect of market structure on adoption speed vary: Levin, Levin, and Meisel (1987), Hannan and McDowell (1984), and Karshenas and Stoneman (1993), respectively, find a negative, positive, and no significant relationship between market concentration and adoption speed. A difficulty in this previous work is accounting for unobserved drivers of both entry and product introduction strategies when identifying the effect of market structure on firms' choices. The entry that occurred in wireless markets after 1996 resulted from regulatory intervention, which limits the role of unobserved profit shifters in determining market structure. In addition, the levels of entry in local markets experienced by 1998 varied because of exogenous differences in geographic features that affect the time required to build a sufficiently dense transmission network. Our empirical finding of a positive relationship between market concentration and adoption speed thus benefits from a more controlled setting than was possible in previous work.

We find that additional competition leads to increased price discrimination both directly, through increased plan variety, and indirectly, through quicker adoption and marketing of the new service, and that both effects are important. In markets with more competition, firms are more likely to upgrade and, if they do, phase out more analog calling plans and introduce more digital calling plans than their counterparts in less competitive markets. We show further that firms decrease the clustering of contracts more in markets with more entry, suggesting that they respond to intensified competition by attempting to steal business rather than by increasing customer segmentation.

We also find that firms increase the number of plans more and spread out plans more evenly for high- than for low-usage customers in markets with more entry. Although business-stealing incentives lead firms to increase plan variety for all consumers, these efforts are more intense for high-usage customers. The indirect role that competition plays in promoting digital upgrading again amplifies this effect; in markets with identical competitive environments, digital adopters offer a larger share of plans targeted at high-usage customers relative to their non-adopting counterparts. High-usage customers also gain more from price decreases due to entry. Consistent with evidence provided by Busse and Rysman (2005), we find that while firms reduce prices in general, quantity discounts are larger in markets with more entry. Competition again plays a direct role, with entry decreasing price, and an indirect role, with firms that offer digital plans also offering steeper discounts than their non-digital competitors.

These results have important consequences for telecommunications regulation. In most countries regulators have a direct impact on market structure through licensing practices, spectrum allocation or auctions, and merger reviews. In determining the number of competitors, it is important for regulators to consider the impact of alternative market structures on the improvement of existing technological standards and subsequent pricing of services. For example, in deciding how much spectrum to make available for wireless broadband services, regulators should consider the incentives that ensuing competition will create for incumbents to phase out narrowband or upgrade existing broadband technologies and the menu of prices they offer for these services. Similarly, the ongoing consolidation in the wireless industry may benefit consumers through improved call quality and coverage and cost savings generated by economies of scale. Our results suggest, however, that increased concentration in local markets may also slow efforts to introduce next-generation services and alter providers' pricing, with high-valuation customers being the most severely affected. Our results complement theoretical work emphasizing that regulators consider the role of substitutes in putting pressure on incumbents to upgrade their offerings (see Riordan 1992). Our work further suggests that regulators consider the subsequent price competition and its relative effects on consumers with different product valuations.

2. Mobile Telecommunications Markets in the Late 1990s

The U.S. cellular phone industry originated in 1981 when the Federal Communications Commission (FCC) awarded two licenses per cellular market area (CMA) to provide cellular telephone services in 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.[2] Between December 1994 and January 1997, the FCC awarded 2,074 PCS spectrum licenses, six each for any given market. The geographic market definition used for PCS spectrum differed from that for cellular markets. Fifty-one major trading areas (MTAs), shown inside bold-faced boundaries in Figure 1, divided the country into regions the size of multiple cities or states, which were subdivided into basic trading areas (BTAs) the same size as or slightly larger than the corresponding CMA. We utilize two snapshots of the universe of residential wireless contracts from the 100 largest CMAs (shown as shaded areas in Figure 1) provided by Kagan World Media to investigate how market conduct changed with entry. The first snapshot was taken in February 1996, when all but two markets operated as duopolies,[3] and the second in March 1998.

Concurrent 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 faced 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, owing to the bankruptcy

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

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

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.[4] This time lag is commonly referred to as the "build-out" delay. Since Nextel's network is cellular-like, similar build-out requirements constrained its national rollout of service. The time it takes to deploy service depends on endogenous market characteristics such as the potential subscriber base and population density. Other characteristics, such as geographic area and terrain features that affect the size of the required tower network and the difficulty of its construction, 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 from 1995 to 1998. By March 1998, on average 4.31 providers offer wireless 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 and the quality and reliability of service. By allowing for new features such as call waiting and caller ID, they increased vertical differentiation in service provision. Prior to the introduction of digital technology, vertical differentiation was primarily due to differences in the quality of service in the local calling area. The only significant horizontal differentiation was brand reputation unrelated to vertical quality.

As of 1998, digital service had limited coverage areas and was frequently restricted to the user's local calling area since the providers' use of four incompatible technology standards increased the chance of inoperability when traveling.[5] Initially, therefore,

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

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

analog service continued to be attractive to low-usage customers or customers who traveled 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 50 percent of subscribers using digital technologies by late 1999 (Cellular Telecommunications and Internet Association 2000).

In 1996 the incumbents employed analog technology almost exclusively, and in rare cases immature digital technologies, and could choose to upgrade their existing analog networks to digital. Adding digital capabilities to an existing network usually 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, which allowed them to avoid the zoning and other difficulties associated with 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.[6] We characterize the upgrade made by such firms as an adoption decision followed by a fixed, brief implementation time.

The timing of and approach of incumbents to digital deployment varied significantly. By 1998, 66.32 percent of all incumbents were offering digital calling plans; 7.77 percent offered only digital plans within a market;[7] and 58.50 percent gave customers a choice between analog and digital technology by offering calling plans for both; 33.68 percent of providers had not yet begun digital deployment by 1998.

The calling plans consist of three-part tariffs. During the sample period most providers held licenses to operate in only a small number of markets. Of the 24 cellular providers in the top 100 markets in 1996, fifteen firms operated in at most five of the top 100 cellular markets, and only five carriers offered service in more than fifteen markets. Because

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

[7] 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.

providers needed to pay other providers to terminate or originate calls outside these limited networks, they offered only local calling plans during the sample period.[8]

To evaluate carriers' nonlinear pricing we define a "plan family" as the set of plans offered by one carrier that differ in their fixed fees and numbers of included peak minutes ("allowances") but have a common service technology and share other features, such as calling area and contract duration. Since regional and national plans were not available, a PCS provider in our data offers one digital "plan family" in a local market, while a cellular provider that has introduced digital service but continues to market analog service offers a choice of two "plan families."

Table 2 shows that a plan family offered by the incumbents in 1996 consisted of, on average, 5.89 individual analog plans; the number of plans offered by a provider ranged from three to eight. By 1998, incumbents had introduced 128 digital plan families across the 98 markets, while continuing to offer 178 analog plan families. 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 shows the variation in fixed fees and allowances across plans in 1998.[9]

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

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[8] With the gradual build-out of larger networks, carriers introduced calling plans with larger regional or national calling areas subsequent to our sample period.

[9] 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 allowance. Along these two dimensions, the plan offerings differ significantly within each plan family.

3. Entry, Technology Adoption, and Nonlinear Pricing: Results

Introducing additional competition into cellular markets has the potential to change firms' nonlinear pricing practices through two channels. With more competition, firms may adjust both the number of options offered to customers in their menu of plans and the placement of their plans. These are the direct effects of entry. At the same time, additional competition may change incumbents' incentives to adopt the digital technology, leading them to make changes to the offered pricing menus if digital plan families differ from analog. These are what we call indirect effects of entry.

To assess these effects of market structure on firms' simultaneous technology and plan variety choices, our empirical analysis relies on a system of equations, "full-information maximum likelihood" (FIML) framework. It allows us to control flexibly for unobserved market attributes that affect entry, technology adoption, and the firms' pricing behavior, which – if left unaccounted for – could lead to spurious correlations. The above-mentioned build-out delay that occurs between the awarding of a license and the activation of service affects primarily the timing of firms' entry behavior, but is uncorrelated with firms' pricing and incumbents' adoption decisions. We use proxies for the difficulty of building out cellular infrastructure as instruments for firms' observed entry decisions to control for the potential endogeneity of entry.

We begin with a discussion of the effects of entry on plan introductions, before turning to an analysis of plan placement, investigating changes in placement overall and comparing changes for customers of different usage types. We then quantify the overall effect on price levels. As we discuss our results, we relate them to the available theoretical predictions.

3.1. Effect on Plan Introductions

We begin our analysis of competition's effect on nonlinear pricing by looking at incumbents' incentives to introduce additional plans. We use the change between 1996 and 1998 in the number of calling plans incumbents offer to test whether they respond to the changes in competition, either directly, by changing the size of plan families, or indirectly, by complementing or replacing existing analog with digital offerings. We find that incumbents were more likely to increase calling plan variety for new or continuing technologies and to phase out additional calling plans for obsolete technologies in markets with more competitors.

Econometric Model. We estimate a system of three nonlinear equations using FIML, which predicts the chosen adjustment in the size of the plan family and technology adoption while controlling for endogenous entry. Our estimation accounts for the discreteness of our data. We specify the change in number of plans between 1996 and 1998, which ranges from -6 to 9 in the data, for incumbent i in market m offering technology $t \in \{analog, digital\}$ as an ordered probit model:

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

where the parameter C^P_l implies a cutoff for the unobservable ξ^P_{imt} that entails moving from a change in plans of $l-1$ to l.[10] We allow the number of entrants to flexibly affect the change in the number of plans by estimating an effect that differs by technology and plan type, controlling for market characteristics:

$$\begin{aligned} f^P\left[\alpha^P, \beta^P, Z^P_{imt}\right] \equiv\ & \alpha^P + \beta^P_1 Prov\_Tech_{im} + \beta^P_2 Plan\_Type_{im} \\ & + \beta^P_3 \left(Prov\_Tech_{im}\right)\left(Plan\_Type_{im}\right)\left(Entrants_m\right) + \beta^P_{\ge 4}\, X^P_{im}. \end{aligned} \tag{2}$$

[10] An alternative specification would be a count-data model. In our setting, the ordered response model has the benefit that it naturally allows for negative values of the outcome variable. See Cameron and Trivedi (2005) for a discussion of the advantages of discrete choice models when modeling changes in counts, and Cameron and Trivedi (1986) for a comparison of the performance of ordered and count-data estimators. A downside to the ordered probit model is that extrapolation beyond the observed maximum change in plans offered is difficult, and we focus on interpreting the effects of changes in the estimated parameters within the observed sample range of the plan change variable only.

$Prov\_Tech_{im}$ 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 family is analog or digital, $Entrants_m$ is the number of PCS entrants in market m by 1998.

We follow earlier studies of the cellular industry, such as Busse (2000) and Miravete and Röller (2004), to control for market demographics that affect firms' choices of plan variety and include these in X_{im}^P. These include the population in market m (Pop_m) as a measure of market size, mean commuting time in minutes in market m $(Commute_m)$ as a proxy for the additional value of a cellular phone to frequent drivers, average household income in market m $(Income_m)$, and the percentage of households in market m whose head of household holds at least a bachelor's degree $(\% \geq BA_m)$. Since plan variety reflects primarily demand heterogeneity, rather than size, we 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.[11] Table 2 provides descriptive statistics for the variables and Table 3 summarizes the variables and their sources. We also include firm fixed-effects in X_{im}^P to control for firm-specific differences in the response to entry.

We specify firm i's decision to adopt digital technology in market m as a probit model:

$$Digital_{im} = \begin{cases} 1 & \text{if } f^D\left[\alpha^D, \beta^D, Z_{im}^D\right] + \xi_{im}^D > 0 \\ 0 & \text{otherwise} \end{cases}. \tag{3}$$

controlling for firm and market factors that might affect adoption:

[11] The incumbents' choices to introduce calling plans may reflect growth or increasing heterogeneity in market demand. Market-specific changes in the cellular subscriber base are unfortunately not available.

$$f^D\left[\alpha^D,\beta^D,Z^D_{im}\right]\equiv\alpha^D+\beta^D_1 Entrants_m+\beta^D_2\%\geq BA_m+\ \beta^D_3 Commute_m+\\ \beta^D_4 Pop_m+\beta^D_5 Income_m+\beta^D_6 National_i+\beta^D_7 Local_i. \tag{4}$$

$Digital_{im}$ equals one if firm i adopted digital technology in market m by 1998. $National_i$ and $Local_i$ indicate whether the firm operates a large or small network defined as more than fifteen and fewer than six markets, respectively. We also include provider fixed-effects. β^D_1 isolates the effect of entry on the incumbents' adoption choices.

Identifying the causal effect that entry has on pricing and adoption is difficult since all potentially reflect the attractiveness of a market in difficult-to-measure ways. If firms choose to build out less competitive markets first, this is likely similarly reflected in incumbents' pricing strategies or the attractiveness of implementing digital technology. For example, in geographic areas with higher demand growth for cellular telephone usage we might expect faster entry and a greater chance of incumbents' upgrading to the digital technology, which allows for greater network capacity. This could introduce a spurious correlation between entry and adoption behavior that does not represent a causal effect.[12]

We control for the possibility of endogenous entry in two ways. First, we consider changes in the number of plans between 1996 and 1998, which removes any market-specific unobservable determinants of the incumbents' pricing strategies that are constant over time. Second, we instrument for the number of entrants in an auxiliary model using several measures of geography and terrain that affect the build-out delay across markets but are uncorrelated with the incumbents' adoption and price discrimination decisions.

We specify the number of entrants in market m, which ranges from 0 to 4 in the data, as an ordered probit model:

[12] While we also control for a possible spurious correlation between entry and plan variety or placement, the theoretical mechanism underlying such correlation is less clear. The effect of market growth on the number of plans or their features is unaddressed in the theoretical literature. There, plan variety is determined by the heterogeneity of horizontal or vertical preferences or both but not by the density of consumers.

$$Entrants_m = \begin{cases} 0 & \text{if } f^E\left[\alpha^E, \beta^E, Z_m^E\right] + \varepsilon_m^E < C_1^E \\ j & \text{if } C_j^E < f^E\left[\alpha^E, \beta^E, Z_m^E\right] + \varepsilon_m^E < C_{j+1}^E, j = 1,2,3 \\ 4 & \text{if } C_4^E < f^E\left[\alpha^E, \beta^E, Z_m^E\right] + \varepsilon_m^E \end{cases} , \quad (5)$$

where the parameter C_j^E implies a cutoff for the unobservable ε_m^E between $j-1$ and j entrants and:

$$f^E\left[\alpha^E, \beta^E, Z_m^E\right] \equiv \alpha^E + \beta_1^E Pop_m + \beta_2^E Pop_m^2 + \beta_3^E Area_m + \beta_4^E Area_m^2 + \beta_5^E \%\, City_m + \beta_6^E AvgElev_m + \beta_7^E StdElev_m. \quad (6)$$

The market's potential subscriber base (Pop_m) 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. We include the market area $\left(Area_m\right)$ and percentage of the market contained in cities as a measure of the degree of urbanization $\left(\%\, City_m\right)$. Difficulty of build-out increases in the former and decreases in the latter. Since the population measure is also included in the technology adoption equation, the excluded instruments are the terrain variability, market area, and degree of urbanization. These factors affect build-out speed (and therefore entry), but are orthogonal to cellular usage demand (and therefore plan variety and features as well as the need for the greater capacity afforded by digital technology).[13]

We assume that the plan change and adoption decision error terms can be decomposed into a market and a firm-(technology-)specific component with $\xi_{imt}^P = \varepsilon_m^P + \eta_{imt}^P$ and

[13] Arguably, degree of urbanization may be correlated with demand independent of our other control variables. To allow for this possibility we re-estimated our 2SLS and system-of-equations FIML specifications including degree of urbanization in the second stage and found very similar results.

$\xi_{im}^{D} = \varepsilon_m^D + \eta_{im}^D$ where $\eta_{imt}^P \sim N(0,1)$ and $\eta_{im}^D \sim N(0,1)$. Normalizing the variance of ε_m^E to one, we allow for a flexible correlation structure between market-level errors:

$$\begin{pmatrix} \varepsilon_m^D \\ \varepsilon_m^P \\ \varepsilon_m^E \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_D^2 & \sigma_{DP} & \sigma_{DE} \\ \sigma_{DP} & \sigma_P^2 & \sigma_{PE} \\ \sigma_{DE} & \sigma_{PE} & 1 \end{pmatrix} \right). \tag{7}$$

ε_m^E, ε_m^D, and ε_m^P are unobservable, market-specific factors that affect the entry, adoption, and plan change decisions, respectively, of all firms in market m. The covariance terms allow for the kinds of correlations in the unobservables discussed above that – in the absence of valid instruments – introduce endogeneity problems in estimating the technology adoption and change in number of plans. The Appendix contains details of the estimation approach.

Direct Effects. The upper left panel of Table 4 shows the results of estimating a system-of-equations FIML specification that controls for the possibility of endogenous entry and allows for the discreteness of the data. Entry has a significant effect on the change in the number of plans offered by both analog-only and mixed-technology providers. 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 0.58 digital plans and remove 0.30 analog plans for each additional entrant. This aspect of our results is complementary to work by Borzekowski, Thomadsen, and Taragin (2009) 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. Incumbents who remain with the analog technology introduce 0.39 additional plans for each additional entrant. These effects are economically significant given means of 5.89 plans and 2.16 entrants in a market. 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 covariates, a one standard deviation increase decreases the number of plans in a market by 0.08 plans for commuting time and by 0.16 plans for income.

The system of nonlinear Equations (1), (3), and (5) is identified even without 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), displayed in the upper right panel of Table 4, and unreported limited information maximum likelihood[14] specifications of the plan variety and adoption equations.

Compared with the FIML results, three of the four entry effects are larger in magnitude using OLS, implying that there are omitted variables associated with entry and with a greater number of plan offerings. Nevertheless, the OLS results are in line with the FIML results: 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. The OLS estimates suggest that analog-only incumbents introduce 0.50 plans for each additional entrant, while the results for digital-technology providers remain insignificant. Of the demand heterogeneity variables, only income heterogeneity has a significant negative effect on the change in the number of calling plans.

Indirect Effects. Entry also has a significant indirect effect on firms' pricing schedules by increasing the likelihood that an incumbent will transition to the digital technology, thereby causing it to reduce the size of or phase out analog plan families and introduce a larger family of digital plans. The lower panels of Table 4 display the FIML and OLS results for the adoption equation. Entry positively affects adoption, with each additional entrant increasing the probability of adoption by 8.06 and 9.59 percentage points, in the FIML and OLS cases, respectively. As in the plan variety equation, the OLS results overstate the effect of entry on adoption due to omitted variables that affect both entry

[14] 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.

and adoption. This could include growth in cellular demand, which would attract entry and lead firms to adopt the higher-capacity digital technology.

The FIML 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 cost savings associated with learning-by-doing or quantity discounts in equipment purchases. Small-scope firms, which are likely to attract consumers who travel less, are less affected by incompatibility of different digital technologies outside their locale, and therefore have greater demand-side incentives to adopt earlier. Adoption is higher in more populous, more wealthy, and less highly educated markets.

Comparing Direct and Indirect Effects. Using these FIML results, we can compare the relative importance of the direct and indirect effects in moving from having no new entrants to having an average level of entry (2.16 firms). This change leads mixed-technology incumbents to phase out an additional 0.65 analog and introduce an additional 1.25 digital plans. The incumbent's probability of adopting the digital technology also increases by 13.46 percentage points. Incumbent firms that transition from analog-only to mixed provider in turn introduce 3.15 digital plans and an additional 0.94 analog plans. Therefore, in expectation, entry indirectly causes a firm to introduce an additional 0.42 digital and 0.13 analog plans.[15] This represents a substantial indirect effect on marketing the new technology and highlights the role of technology choice as a second avenue through which market structure affects firms' nonlinear pricing strategies.

Our results on technology adoption are of independent interest as they are consistent with theoretical predictions. In the Appendix, we consider a model of strategic technology adoption in the spirit of Fudenberg and Tirole (1986). Anticipating future entry by PCS firms, the cellular incumbent chooses the optimal time to introduce digital service, which we model as a product innovation. In contrast to Fudenberg and Tirole (1986), we focus

[15] A similar calculation for transition to a digital-only provider yields a direct effect of 0.03 and an expected indirect effect of 0.45 plan introductions.

on entrants who have pre-committed to digital technology, eliminating a strategic deterrence motive in the incumbent's decision. The model predicts that the incumbent's adoption timing hinges on the sensitivity of its post-entry profits to its decision. If increased competition from additional firms dramatically reduces the incumbent's profits from the old technology relative to those from the new technology, it is more likely to adopt before entry occurs. Our empirical results thus suggest that the onset of PCS competition has a greater adverse effect on incumbents' profits from analog service than on their profits from digital offerings. This is probably because of the fast consumer uptake of digital service discussed earlier and is likely the case in information and communications services industries more broadly. In these industries, revenues from new technologies tend to quickly overtake those from old, and the price of old technologies is more sensitive to increased competition than the price of new.

These results are also 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. Together 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 how it affects adopters' market shares and ability to deter entry.[16]

3.2. Effect on Plan Placement

Our results so far demonstrate that entry led to finer price discrimination as measured by the size of a plan family. Since the size on its own does not provide information about which types of consumers are targeted with different plans, we now test the effect of entry on the placement of calling plans across the usage spectrum. We find that, with more entry, firms spread their plans more evenly over the usage spectrum. This behavior is consistent with business-stealing overpowering the firm's incentive to differentiate

[16] Hannan and McDowell (1984), Karshenas and Stoneman (1993), Oster (1982), and Rose and Joskow (1990) investigate the effect of firm characteristics on adoption speed. Apart from firms' geographic scope, we cannot examine this question because firms' subscriber bases, revenues, and network sizes by market are unavailable.

under increased competition. This result reinforces the plan change results and confirms that they are not due to counting very similar plans as distinct.

To measure plan placement, we use a Herfindahl index based on the share of minutes "allocated" to each plan. We chose the Herfindahl index as a measure of clustering because, once normalized, it is comparable across plan families. While it would be useful to compare the plan variety observed in our data with that predicted by theory, this is currently not possible given the state of the theoretical literature. Given the lack of theoretical guidance, we rely on a more descriptive measure of plan clustering. Our goal is to measure, plan-family-by-plan-family, the closeness of plans across different markets in the same industry, while controlling for the fact that plans might be closer together in a particular market because of heterogeneous preferences. To do so we use the Herfindahl index as the dependent variable in a regression that appropriately controls for heterogeneity of consumer preferences using observable market attributes.

We assume that the total allocable minutes within a plan family equals the largest allowance on any plan within the plan family.[17] We define the minutes allocated to a plan as the difference between the plan's allowance and the closest smaller allowance in the plan family (or zero for the first plan). For example, if a plan family includes two plans with allowances of 300 and 500 minutes, the Herfindahl index is $\left((500-300)/500\right)^2+\left((300-0)/500\right)^2=13/25$. For a plan family with n plans, the Herfindahl index ranges from a value of $1/n$ if all plans are equally spaced to a value of 1 if all plans are identical.

To make the Herfindahl index comparable across different-sized plan families, we normalize the Herfindahl by dividing it by the Herfindahl that results from equal spacing

[17] As a robustness check, we replicate our results using as an alternative measure of allocable 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. To check the sensitivity of the results to this assumption, we estimate assuming a maximum usage of either 1,000 or 2,000 minutes. The results are similar to the ones in Table 6 in terms of both magnitude and significance of the coefficients regardless of the assumption of maximum usage.

of plans (1/*n*). In our example above, the normalized Herfindahl is $\left(13/25\right)/\left(1/2\right) = 26/25$. For a plan family with *n* plans, the normalized Herfindahl ranges from one, if all plans are equally spaced, to n, if all plans are identical. The top panel of Table 5 provides summary statistics, using both entrants' and incumbents' 1998 offerings, which increases the number of observations to 521 plan families.

Econometric Model. We use a setup similar to the plan change model and specify the firms' choices of plan placement as:

$$\begin{aligned} NormHHI_{imt} &= \alpha^{H} + \beta_{1}^{H} Prov\_Tech_{im} + \beta_{2}^{H} Plan\_Type_{im} \\ &\quad + \beta_{3}^{H} \left(Prov\_Tech_{im}\right)\left(Plan\_Type_{im}\right)\left(Entrants_{m}\right) + \beta_{\geq 4}^{H} X_{im}^{H} + \xi_{imt}^{H} \\ &\equiv f^{H}\left[\alpha^{H}, \beta^{H}, Z_{imt}^{H}\right] + \xi_{imt}^{H}, \end{aligned} \tag{8}$$

where $NormHHI_{imt}$ is the normalized Herfindahl index of plan placement in 1998. We employ levels instead of heterogeneity measures for the demographic variables to capture how overall demand affects firms' choice of plan spacing. We again estimate the system of Equations (3), (5), and (8) using FIML, accounting for the simultaneous choice of technology adoption by firms and instrumenting for entry. The Appendix describes the adjustments made to the estimation procedure to reflect the continuous nature of the normalized Herfindahl measure that replaces the discrete plan change variable.[18]

Direct and Indirect Effects. Competition has a significant and negative direct effect on the normalized Herfindahl for all plan family types, except for digital offerings by mixed-technology providers. These results, shown in the left-hand columns of Table 6, are also economically significant. As a share of the mean across all plan families, an additional competitor decreases the normalized Herfindahl by 8.32 to 13.22 percent of its mean, depending on plan family type and provider technology. Increased competition leads firms to spread plans more evenly across the usage spectrum, increasing plan variety.

[18] We do not include entrants' choice of technology in estimating Equation (3) since entrants pre-commit to the digital technology.

The indirect effect of competition reinforces the direct effect, leading firms to increase plan variety. Transitioning from analog-only to a mixed-technology provider leads to a decrease of 0.28 (14.53 percent of the mean) in the analog and a decrease of 2.26 (116.52 percent of the mean) in the digital normalized Herfindahl. These estimates indicate that the indirect effects of competition also lead to less clustered plan families.

For mixed providers, direct effects have more impact on analog offerings, while indirect effects are more important for digital offerings. The average increase in the number of competitors entails a direct reduction of 0.35 in the normalized Herfindahl for analog plan families and no statistically significant effect for digital plan families. Indirectly, each additional entrant increases the probability of adoption by 4.98 percentage points. Therefore, accounting for the increased likelihood of digital adoption due to entry entails an additional decrease of 0.01 in the analog and a decrease of 0.11 in the digital normalized Herfindahl in expectation.[19]

Robustness. To test the robustness of our results to the plan placement measure, we re-estimate using the non-normalized Herfindahl index and restricting the sample to plan families with five to seven plans. This reduces the number of observations to 335. Summary statistics are in the top panel of Table 5 and the results are shown in the right-hand columns of Table 6. The results for plan families in single-technology offerings are directionally consistent with those using the full sample. For this sub-sample, the average Herfindahl in markets without entry is equivalent to 2.79 equally spaced plans. The average level of entry increases this to 4.21 for analog plan families and 3.14 for digital families. The results in mixed-technology offerings are not significant, possibly because there are very few observations in the restricted subset.[20]

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[19] A similar calculation for transition to a digital-only provider yields a direct effect of -0.38 and an expected indirect effect of -0.07.

[20] To ensure that our results are not sensitive to our specific choice of agglomeration measure, we re-estimated using a modified L-function index developed by Marcon and Puech (2003) for use in measuring industry agglomeration. We adapted the L-function index to our one-dimensional, linear setting rather than the circular setting needed in industry agglomeration. The results using the L-function index are qualitatively similar, and generally stronger, than the estimates using the Herfindahl index.

3.3. Heterogeneous Effects on Consumers

Thus far we have found that entry increases the number of plans offered by incumbent firms and spreads these plans more evenly across the usage spectrum. We now test whether increases in competition have a differential effect on high- versus low-valuation consumers. Using several different measures of plan variety and placement, we find that increased competition benefits high- more than low-valuation consumers.

To test the relative effect on high-valuation consumers, our primary measure is the share of "high-usage" plans in a plan family. We designate a calling plan as high-usage if its allowance is greater than 180, the median allowance across all plans in our sample. We again include both entrants and incumbents to increase the number of observations and focus on levels since all entrants had zero plans in 1996. Summary statistics for the measures are in the bottom panel of Table 5. As in our other models, we specify the firms' choices of plan mix as a function of the provider's technology type, the plan family's technology, and flexible entry effects that vary by provider type and technology, controlling for market demographics. We jointly estimate the determinants of the share of high-usage plans together with the determinants of firms' adoption decisions (Equation 3) and the aggregate entry determinants (Equation 5) using FIML.

Direct and Indirect Effects. We find that the share of high-usage plans increases significantly with the number of competitors for all provider types. The results are shown in the left-hand columns of Table 7. The average share of high-usage plans is 55.30 percent. An additional competitor increases the share by 3.13 to 6.60 percentage points, depending on the plan family and provider type. This is a large effect given that the number of competitors ranges from two to six.

These results are consistent with theoretical predictions. For digital plans, we find that firms increase the number of plans offered in markets with more entry (see Table 4), consistent from a theoretical perspective with firms competing in a regime of relatively low horizontal differentiation. Firms are sufficiently similar such that, with more entry, the incentive to grab market share (by introducing plans and decreasing their clustering) exceeds the incentive to increase prices to loyal customers (by removing plans or increasing plan clustering).[21] Yang and Ye (2008) predict that this business stealing incentive manifests itself more at the high end of the quality spectrum – or here, the usage spectrum – where the strong vertical tastes of high-valuation consumers overcome the horizontal differentiation between the firms. Thus we would expect firms not only to expand offerings overall but to expand them more at the high end than at the low end as we find.

Entry also has a significant indirect effect on the share of high-usage plans for digital plan families. For a mixed provider, the share of digital plans above the median is 48.52 percent and for a digital-only provider 36.06 percent. These greatly exceed the 12.88 percent for analog-only plan families. Transitioning to a mixed provider has a negligible effect on the share of analog plans above the median.

We can also compare the relative importance of the direct and indirect effects for a mixed-technology provider at the average level of entry. Entry directly increases the share of plans above the median by 7.95 percentage points for analog and by 6.75 percentage points for digital families. Each additional entrant increases the probability of adoption by 28.59 percentage points. Therefore, in expectation the indirect effects increase the share of digital plans by 13.87 percentage points, but have no significant effect on the share of analog plans.[22]

Robustness. To ensure that the plans targeting high-valuation consumers are distinct, we also employ a Herfindahl index, normalizing it by the index if all plans above the median were equally spaced. We base the Herfindahl index on the spectrum of minutes from the

[21] The reduction in analog plan offerings is consistent with firms competing in a regime of relatively high horizontal differentiation. However, the pricing of analog plans also reflects the technology's retirement, which likely overwhelms the pure differentiation effects.

[22] A similar calculation for transition to a digital-only provider yields a direct effect of 14.26 and an expected indirect effect of 10.31 percent percentage points in the share of plans above the median.

allowance just below the median (180 minutes) to the largest allowance within the plan family. For example, consider a plan family with plans having allowances of 100, 200, and 500 minutes. There are two plans with above-median allowances and (500–100) minutes, or 400 minutes, of allocable usage. The resulting Herfindahl index is $\left((500-200)/400\right)^2 + \left((200-100)/400\right)^2 = 5/8$. To normalize the Herfindahl we divide by $1/2$, the Herfindahl if the two plans above the median were equally spaced, to obtain a normalized Herfindahl of $5/4$. The econometric specification is that given by Equation (8) but with $HiNormHHI_{imt}$ replacing $NormHHI_{imt}$.

Theoretically, this measure ranges from a minimum of 1 when high-usage plans are equally spaced, to *n*, when all *n* high-usage plans are identical.[23] In our data, it ranges from 1.00 to 3.02. The estimation results using this measure are shown in the middle columns of Table 7. Entry has a negative and significant direct effect on the normalized Herfindahl index for all plan family types. Relative to the average normalized Herfindahl above the median across all plan families (1.33), each additional competitor reduces the normalized Herfindahl by 5.34 to 12.05 percent, depending on the plan family and provider type. The indirect effect of competition is negative but not significant.

As a further robustness check, we use the non-normalized Herfindahl and restrict the analysis to plan families with five to seven plans. The results, displayed in the right-hand columns of Table 7, are qualitatively similar although not as significant for mixed providers owing to the reduced amount of data. Across specifications, we thus find that competition leads firms to introduce additional, more evenly spaced, high-usage plans.

3.4. Effect on Price Levels

Our finding that competition significantly alters the nonlinear pricing practices of cellular firms raises the question of how price levels are affected overall and across different

[23] 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.

consumers. We follow the approach of Busse and Rysman (BR) (2005) to assess the effect of competition on quantity discounting.[24] 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. Overall, we find that increased competition results in greater price reductions for high-usage consumers.

Econometric Model. BR suggest testing 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:

$$\ln(P_{ijmt}) = \alpha_{imt} + \beta_{imt} \ln(q_j) + \varepsilon_{ijmt}, \tag{9}$$

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 (9), 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 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. 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 2,000-minute cutoff.

[24] In related work, McManus (2007) provides empirical evidence for the "no distortion at the top" prediction of theoretical models of nonlinear pricing.

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 (9) for each plan family using OLS. This generates a distribution of estimates for α and β based on 521 plan families, summarized in Table 8. All plan families exhibit quantity discounting, with digital plan families exhibiting more discounting than analog. In the second stage, we follow BR in assessing how the estimated curvature of the pricing schedule changes with competition by estimating:[25]

$$\begin{aligned} Beta_{imt} &= \alpha^C + \beta_1^C Prov\_Tech_{im} + \beta_2^C Plan\_Type_{im} \\ &\quad + \beta_3^C \left(Prov\_Tech_{im}\right)\left(Plan\_Type_{im}\right)\left(Entrants_m\right) + \beta_{\geq 4}^C X_{im}^C + \xi_{imt}^C \\ &\equiv f^C\left[\alpha^C, \beta^C, Z_{imt}^C\right] + \xi_{imt}^C. \end{aligned} \tag{10}$$

We augment Equation (10) with our usual adoption and entry equations, Equations (3) and (5), in a system-of-equations FIML.

Direct and Indirect Effects. The results, shown in Table 9, suggest that the increased number of plans targeting high-usage customers is associated with lower prices.[26] Competition directly 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 0.05 for analog-only providers and 0.04 for digital-only providers, relative to an average curvature of 0.63 and 0.48, respectively. Competition also has a significant indirect effect on quantity discounting. Transitioning from an analog to a mixed provider decreases the curvature of the analog pricing schedule by 0.08 and introduces a digital pricing schedule that has a much greater

[25] Our estimation of the second stage 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.

[26] 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 (10) 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.

curvature (by 0.34) than the original analog pricing schedule. Firms transitioning to full digital service offer a digital pricing schedule with a curvature 0.22 below that of an analog-only provider.

We can again compare the relative importance of the direct and indirect effects for a mixed-technology provider due to the average level of entry. The direct effect of entry is to decrease the curvature for analog plan families (by 0.04) and digital plan families (by 0.02). In expectation, entry indirectly decreases the curvatures of analog and digital plan families by 0.01 and 0.03, respectively, by accelerating technology adoption. The indirect and direct effects are thus similar in importance in affecting price levels.[27]

4. Conclusion

Firms in communications and information services industries usually market their products using nonlinear pricing plans and frequently introduce new generations of services. How market structure affects these interdependent choices is assessed by two relevant but distinct strands of literature: one focused on market structure's effect on product diffusion and another on its effect on second-degree price discrimination. We empirically estimate market structure's joint effect on adoption and pricing to quantify their relative effects. We examine the effect of entry on firms' pricing responses in the context of new technology diffusion. Our setting allows us to control for unobservable determinants of both the market structure and the behaviors of interest. We find economically significant effects of market structure on both adoption and pricing.

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 anticipating that significant entry of digital

[27] A similar calculation for transition to a digital-only provider yields a direct effect of -0.08 and an expected indirect effect of -0.02.

competitors would largely eliminate the market for analog service. The incentive provided by competition 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 by offering more plans and spreading their plans more evenly across the usage spectrum. This is consistent with firms' incentive to "fill the calling plan space" by stealing customers whose needs were not closely served by their pre-existing menu of calling plans, despite the narrower segmentation of the market among firms. Firms compete most fiercely for high-volume customers.

Our results on the interaction between firms' pricing strategies and technology adoption suggest the need for a more detailed analysis of the effect of technology adoption on subscribers' usage choices and therefore consumer welfare. Usage data would also allow a more detailed analysis of competition's effect on the nonlinear pricing plans available to different customer types and therefore a welfare assessment of the effect of plan variety.

5. Appendix

5.1. 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 a new technology.[28] We tailor a subgame of the Fudenberg and Tirole (FT) (1986) model to 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 the pre-existing technology in the meantime.[29]

We apply the model to information and communications services industries, such as cellular services, which share the following characteristics. First, competition in these industries can be regarded as differentiated Bertrand since output can be changed easily once capacity is set and marginal costs are nearly zero in the absence of capacity constraints. Second, most innovations in these industries are product rather than process innovations since marginal production costs are nearly zero.[30] Finally, in these industries, post-entry profits under the old technology are usually more adversely affected by entry than those under the new technology, as we discuss below. Given these assumptions, we find that the incumbent's propensity to adopt prior to entry increases in the number of entrants, at least when faced with many entrants.

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 FT, we assume that $\Pi_0^I < \Pi_1^I$. $f(t)$ denotes the one-time cost of adopting the technology, which is

[28] In addition to being unable to deter entry, the incumbents' ability to delay entry in our setting is also limited since the FCC required PCS license holders to meet specific coverage requirements within a five-year time window to maintain their licenses.

[29] As in FT, 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 incumbent's reaction to entry.

[30] Although the digital technology reduces the cost of providing cellular services through better capacity management, such cost reductions are largely unaffected by the number of competitors. In contrast, FT assume that the innovation reduces costs.

decreasing and convex in the adoption time. The optimal time of adoption, t_1, occurs when:

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

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

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

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

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

Simplifying, we get:

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

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:

$$\frac{d\left(V_1 - V_3\right)}{dn} = \left(\frac{e^{-rt_2} - e^{-rt_3}}{r}\right)\frac{d\left(\Pi_1^E - \Pi_0^E\right)}{dn}. \tag{A6}$$ [31]

[31] 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.

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.

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 the two services are substitutes, so that $dp_0^E/dn, dp_1^E/dn < 0$.

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.[32] Then we can decompose the effect of entry on incremental flow profits as:

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

This expression simplifies to:

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

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

[32] If the incumbent adopts the digital technology, consumers cannot substitute to the analog technology. In information and communications services, the new technology usually supplants the old.

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 exceed those from old-technology service and the two services are not close substitutes.

In information and communications services industries, there are a number of reasons why post-entry profits under the old technology are likely more adversely affected by entry than those under the new technology. In these industries, revenues from new services tend to quickly exceed those of previous technologies. As discussed in Section 2, the number of subscribers to digital quickly overtook those to analog service, suggesting that analog-service demand declined significantly in the presence of even a few entrants. New entrants usually offer the latest technology, as they did in cellular services, suggesting that the price of the new service is more sensitive to the number of entrants than the price of the old service. Lastly, the elasticity of the incumbents' residual demand elasticity for the new service is likely greater than its residual demand elasticity on the old service, at least if it faces significant entry. In cellular services incumbents faced on average 2.16 entrants.

5.2. Estimation Procedure

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

$$L = \prod_{m=1}^{M} L_m \ . \tag{A9}$$

In estimating the system of equations with the number of plan introductions as our dependent variable, the contribution to the likelihood from market m is:

$$L_m = \Pr\left(Entrants_m = j,\ Digital_{im} = k_i,\ \Delta Plans_{imt} = l_{it}\ \forall i,t \right), \tag{A10}$$

where j is an index of the number of entrants in market m, k_i equals one if firm $i \in \{1,2,...,I\}$ implements the digital technology in market m and zero otherwise, and l_{it} indexes the change in the number of plans in firm i's plan family for technology $t \in \{\text{analog,digital}\}$ in market m. This equals:

$$\begin{aligned} \Pr\Big(& C_j^E - f^E < \varepsilon_m^E < C_{j+1}^E - f^E,\ \ \xi_{im}^D < (2k_i - 1) f_i^D, \\ & C_{l_{it}}^P - f_{it}^P < \xi_{imt}^P < C_{l_{it}+1}^P - f_{it}^P \ \ \forall i,t \Big), \end{aligned} \tag{A11}$$

where C_j^E is the cutoff for j entrants and C_l^P is the cutoff for a change of l in the number of plans offered. This probability is given by the integral of the $3I+1$-dimensional[33] normal distribution of ξ_{im}^D, ξ_{imt}^P, and ε_m^E with mean zero and variance-covariance matrix given by (I is the identity matrix and Ξ is a matrix of all ones):

$$\Sigma = \begin{bmatrix} \sigma_D^2 \Xi_{I\times I} + \mathrm{I}_{I\times I} & \sigma_{DP}\Xi_{I\times 2I} & \sigma_{DE}\mathrm{I}_{I\times 1} \\ \sigma_{DP}\Xi_{2I\times I} & \sigma_P^2\Xi_{2I\times 2I} + \mathrm{I}_{2I\times 2I} & \sigma_{PE}\mathrm{I}_{2I\times 1} \\ \sigma_{DE}\mathrm{I}_{1\times I} & \sigma_{PE}\mathrm{I}_{1\times 2I} & 1 \end{bmatrix}, \tag{A12}$$

over the surface defined by f^D; f^P and the cutoffs C_{-5}^P through C_9^P; and f^E and the cutoffs C_1^E through C_4^E that are consistent with the observed technology, change in plans offered, and number of entrants, respectively. The variance-covariance matrix in Equation (A12) allows for correlation in the unobservable market shifters of the adoption,

[33] This results from stacking the I adoption errors ξ_{im}^D, the $2I$ technology-specific plan-change errors ξ_{imt}^P and the single market-level error ε_m^E. The dimensionality of the plan change errors is less than $2I$ in the data since not all firms offer both analog and digital plan families in all markets.

plan change, and entry equations, and thus controls for the endogeneity of market structure across equations.

The assumption that $\xi_{im}^{D} = \varepsilon_{m}^{D} + \eta_{im}^{D}$ and $\xi_{imt}^{P} = \varepsilon_{m}^{P} + \eta_{imt}^{P}$ with $\eta_{im}^{D} \sim N\left(0,1\right)$ and $\eta_{imt}^{P} \sim N\left(0,1\right)$ allows us to simplify the likelihood by integrating out η_{im}^{D} and η_{imt}^{P}. This results in:

$$L_m = \int_{C_j^E - f^E}^{C_{j+1}^E - f^E} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \prod_{i=1}^{I} \left[g_i^D\left(\varepsilon^D\right) \prod_{t \in \{A,D\}} g_{it}^P\left(\varepsilon^P\right) \right] \phi\left(\varepsilon^D, \varepsilon^P, \varepsilon^E\right) d\varepsilon^D d\varepsilon^P d\varepsilon^E, \tag{A13}$$

where

$$\begin{aligned} g_i^D\left(\varepsilon^D\right) &= \Phi\left(f_i^D + \varepsilon^D\right)^{k_i} \left(1 - \Phi\left(f_i^D + \varepsilon^A\right)\right)^{1-k_i} \\ g_{it}^P\left(\varepsilon^P\right) &= \Phi\left(C_{l_{it}+1}^P - f_{it}^P - \varepsilon^P\right) - \Phi\left(C_{l_{it}}^P - f_{it}^P - \varepsilon^P\right), \end{aligned} \tag{A14}$$

and $\phi\left(\varepsilon^D, \varepsilon^P, \varepsilon^E\right)$ refers to the pdf of the trivariate normal distribution of ($\varepsilon^D, \varepsilon^P, \varepsilon^E$) in Equation (7). We further integrate ε_m^E out of the likelihood, conditioning on ε_m^D and ε_m^P to obtain:

$$\begin{aligned} L_m = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \prod_{i=1}^{I} &\left[g_i^D\left(\varepsilon^D\right) \prod_{t \in \{A,D\}} g_{it}^P\left(\varepsilon^P\right) \right] \times \\ &\left[\Phi_{\varepsilon^E|\varepsilon^D,\varepsilon^P}\left(C_{j+1}^E - f^E\right) - \Phi_{\varepsilon^E|\varepsilon^D,\varepsilon^P}\left(C_j^E - f^E\right) \right] \phi\left(\varepsilon^D, \varepsilon^P\right) d\varepsilon^D d\varepsilon^P \end{aligned} \tag{A15}$$

where $\Phi_{\varepsilon^E|\varepsilon^D,\varepsilon^P}$ denotes the conditional cdf of ε^E, given realizations of ε^D and ε^P.

For the continuous plan variety measures, the likelihood of observing the firms' technology adoption and plan variety choices across plan technologies in market m becomes (where v_{it} equals the observed variety measure for firm i's plan family for technology t in market m):

$$\begin{aligned} &\Pr\left(Entrants_m = j,\ Digital_{im} = k_i,\ Variety_{imt} = v_{it}\ \forall i,t\right) = \\ &\quad \Pr\left(C_j^E - f^E < \varepsilon_m^E < C_{j+1}^E - f^E,\ \xi_{im}^D < \left(2k_i - 1\right) f_i^D,\ \xi_{imt}^P = v_{it} - f_{it}^P\right). \end{aligned} \tag{A16}$$

This entails only one modification of $g_{it}^P\left(\varepsilon^P\right)$ above, which now equals the standard normal pdf of η_{imt}^P:

$$g_{it}^{P}\left(\varepsilon^{P}\right)=\phi\left(v_{it}-f_{it}^{P}-\varepsilon^{P}\right). \tag{A17}$$

For a given value of the parameters, we use simulation techniques to compute each market's contribution to the likelihood in Equation (A15) by integrating numerically over the bivariate normal distribution of ε^{D} and ε^{P}. We then use a numerical maximization routine to maximize the full likelihood in Equation (A9) and update the parameters until convergence.

We assess parameter significance using bootstrap samples of 50 replications. We control for non-random clustering of unobservables by firm. 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 its market. 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.

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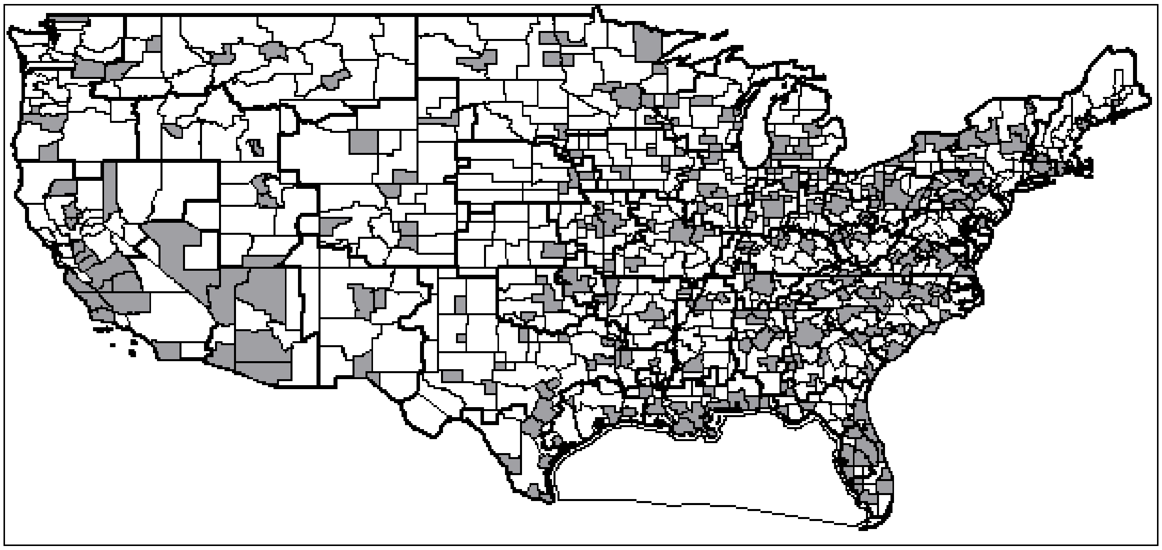
7. Figures and Tables

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
Top 100 Cellular Markets, Q4 1995 – Q2 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

Descriptive Statistics, 98 Cellular Markets

Variable	Obser-vations	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
Allowance (Number of Included 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:

$$\text{Herfindahl Index} = \sum_{j=1}^{J}\left(\frac{\bar{q}_j - \bar{q}_{j-1}}{\bar{q}_J}\right)^2$$ where $\bar{q}_j$ denotes the allowance on tariff j 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 and Digital Technology Adoption by Cellular Incumbents, 1996-1998

	FIML			OLS	
	Coeff.	Std. Error	Marginal Effect	Coeff.	Std. Error
Plan Change Equation					
Technologies offered by Provider in 1998					
Prov_Analog	-0.6411 **	0.3488	-0.9342	-1.4216	1.0966
Prov_Mixed	0.0021	0.3292	0.0031	0.1127	1.0201
Plans' Type of Technology					
Plans_Digital	2.1613 ***	0.2486	3.1493	3.0159 ***	0.3615
Market Characteristics					
Prov_Analog*Entrants	0.2667 **	0.1156	0.3886	0.4983 **	0.2218
Prov_Digital*Entrants	0.1080	0.1652	0.1573	0.2678	0.4285
Prov_Mix.*Plans_An.*Entrants	-0.2056 **	0.0964	-0.2996	-0.4416 **	0.2001
Prov_Mix.*Plans_Dig.*Entrants	0.3969 ***	0.0895	0.5783	0.4844 ***	0.0829
Population	-0.0016	0.0041	-0.0023	0.0036	0.0098
Demand Heterogeneity Measures					
Het. in Commuting Time	-0.0523 ***	0.0046	-0.0762	-0.1038	0.1643
Het. in Household Income	-0.4680 ***	0.0039	-0.6819	-0.7202 **	0.3231
Het. in Educational Attainment	-0.0010	0.0041	-0.0014	-0.0148	0.0676
Digital Adoption Decision Equation					
Market Characteristics					
Entrants	0.3067 *	0.1957	0.0806	0.0959 *	0.0522
% with B.A. or more	-0.0406 **	0.0180	-0.0107	-0.0081	0.0097
Commuting Time	0.0058	0.0262	0.0015	0.0055	0.0162
Population	0.0442 ***	0.0142	0.0116	0.0039 **	0.0017
Household Income	0.0429 ***	0.0149	0.0113	0.0108 **	0.0053
Provider Characteristics					
Large Geographic Scope	2.3537 ***	0.3953	0.6182	0.1901 ***	0.0368
Small Geographic Scope	1.7787 ***	0.4102	0.4672	-0.2634 **	0.1038
Adj. R-Squared (Plan Change)				0.7392	
Observations (Plan Change)				306	
Adj. R-Squared (Digital Adoption)				0.3877	
Observations (Digital Adoption)				193	
Log-Likelihood (FIML)		-748.16			
Observations (FIML)		306			

Selected provider fixed effects included in plan change and digital adoption decision equations. Standard errors are clustered at the provider level and are based on 50 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:

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

and for the system-of-equations specification:

$$ENTRANTS = \underset{(0.0291)}{0.1408}\,POP - \underset{(0.0003)}{0.0012}\,POP^2 + \underset{(0.0845)}{0.1625}\,AREA - \underset{(0.0053)}{0.0034}\,AREA^2 + \underset{(0.7698)}{0.5147}\%CITY - \underset{(0.2719)}{0.2563}\,ELEV\text{-}AVG - \underset{(0.8331)}{0.8762}\,ELEV\text{-}SD + \varepsilon^E,$$

with estimated covariances $\{\sigma_{DE}, \sigma_{EP}, \sigma_{DP}\} = \{0.020, -0.088, -0.007\}$ and estimated variances $\{\sigma^2_D, \sigma^2_P\} = \{0.054, 0.043\}$. 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: 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	521
"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 6: Placement of Incumbents' and Entrants' 1998 Pricing Plans Based on Allowance Levels: 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	-0.6456 **	0.2926	0.0730	0.0703
Prov_Mixed	-0.9270 ***	0.1865	-0.1320 ***	0.0465
Entrant	0.3543 ***	0.1299	0.0439	0.0357
Plans' Type of Technology				
Plans_Digital	-1.3289 ***	0.1631	-0.0438	0.0431
Market Structure				
Prov_Analog*Competitors	-0.2560 ***	0.0617	-0.0558 ***	0.0176
Prov_Digital*Competitors	-0.1745 ***	0.0391	-0.0185 *	0.0132
Prov_Mixed* (Plans_Analog)*Competitors	-0.1611 ***	0.0509	0.0011	0.0141
Prov_Mixed* (Plans_Digital)*Competitors	0.0493	0.0446	0.0026	0.0129
Demand Characteristics				
Percent with B.A. or more	0.0039 ***	0.0008	0.0005 *	0.0004
Commuting Time	-0.0261 ***	0.0029	-0.0040 *	0.0027
Population	-0.0053 **	0.0026	-0.0063 **	0.0032
Household Income	-0.3187 ***	0.0030	-0.0498 ***	0.0029
Std. deviation, η^{Herf}	0.5503 ***	0.0393	0.0830	0.0779
Log-Likelihood	-622.90		190.94	
Observations	521		335	

Selected provider fixed effects included in plan variety and digital adoption decision equations. Provider-level clustered standard errors based on 50 bootstrapped samples. * = 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:

$$ENTRANTS = \underset{(0.0225)}{0.1640}\,POP - \underset{(0.0002)}{0.0015}\,POP^2 + \underset{(0.0996)}{0.1373}\,AREA - \underset{(0.0072)}{0.0023}\,AREA^2 + \underset{(1.0101)}{0.1889}\,\%CITY - \underset{(0.2779)}{0.4776}\,ELEV\text{-}AVG + \underset{(0.6056)}{0.6585}\,ELEV\text{-}SD + \varepsilon^E$$

$$ADOPTION = \underset{(0.1127)}{0.1823}\,ENTRANTS - \underset{(0.0226)}{0.0473}\,BAPLUS - \underset{(0.0265)}{0.0348}\,COMMUTE + \underset{(0.0180)}{0.0600}\,POP + \underset{(0.0170)}{0.0449}\,INCOME + \underset{(0.3971)}{2.7294}\,LARGE\text{-}SC + \underset{(0.4090)}{1.9737}\,SMALL\text{-}SC + \xi^D,$$

and for Specification II:

$$ENTRANTS = \underset{(0.0308)}{0.1639}\,POP - \underset{(0.0003)}{0.0015}\,POP^2 + \underset{(0.1016)}{0.1489}\,AREA - \underset{(0.0068)}{0.0033}\,AREA^2 + \underset{(1.8066)}{0.8372}\,\%CITY + \underset{(0.3841)}{0.2186}\,ELEV\text{-}AVG + \underset{(0.7769)}{0.2846}\,ELEV\text{-}SD + \varepsilon^E$$

$$ADOPTION = \underset{(0.1694)}{0.2136}\,ENTRANTS - \underset{(0.0332)}{0.0691}\,BAPLUS + \underset{(0.0334)}{0.0100}\,COMMUTE + \underset{(0.0246)}{0.0601}\,POP + \underset{(0.0228)}{0.0486}\,INCOME + \underset{(1.2338)}{2.0507}\,LARGE\text{-}SC + \underset{(0.9086)}{0.8222}\,SMALL\text{-}SC + \xi^D$$

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 covariances $\{\sigma_{DE}, \sigma_{EP}, \sigma_{DP}\}$ are {0.046,0.138,-0.010} for Specification I and {0.030,0.003,-0.015} for Specification II. The estimated variances $\{\sigma^2_D, \sigma^2_P\}$ are {0.016,0.073} for Specification I and {0.011,0.051} for Specification II.

Table 7: 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	0.1288 *	0.0967	0.0924	0.1583	0.0827	0.0785
Prov_Mixed	0.1246 **	0.0518	0.0655	0.1448	-0.2736 ***	0.0678
Entrant	-0.1913 ***	0.0319	-0.0749 **	0.0413	0.0778 *	0.0485
Plans' Type of Technology						
Plans_Digital	0.3606 ***	0.0531	-0.1029	0.1085	-0.1401 ***	0.0444
Market Structure						
Prov_Analog*Competitors	0.0498 ***	0.0175	-0.1602 ***	0.0286	-0.0889 ***	0.0264
Prov_Digital*Competitors	0.0660 ***	0.0126	-0.0710 ***	0.0260	-0.0548 ***	0.0176
Prov_Mixed* (Plans_Analog)*Competitors	0.0368 **	0.0145	-0.1369 ***	0.0247	-0.0005	0.0235
Prov_Mixed* (Plans_Digital)*Competitors	0.0313 **	0.0125	-0.0721 **	0.0324	-0.0044	0.0235
Demand Characteristics						
Percent with B.A. or more	-0.0018 ***	0.0007	0.0008	0.0008	0.0012 *	0.0009
Commuting Time	0.0012	0.0018	0.0104 ***	0.0028	-0.0005	0.0026
Population	0.0072 ***	0.0023	0.0008	0.0034	-0.0056 *	0.0034
Household Income	-0.0046 ***	0.0015	-0.0053 **	0.0021	0.0033 **	0.0017
Std. deviation, η^Y	0.1354 ***	0.0247	0.3224 ***	0.0248	0.1293 ***	0.0469
Log-Likelihood	101.20		-327.63		35.91	
Observations	521		504		335	

Selected provider fixed effects included in plan variety and digital adoption decision equations. Provider-level clustered standard errors based on 50 bootstrapped samples. * = 10% significance, ** = 5% significance, *** = 1% significance. The estimated coefficients of the auxilliary equations with the corresponding bootstrap standard errors in parentheses are for Specification I:

$$ENTRANTS = \underset{(0.0258)}{0.1688}\,POP - \underset{(0.0003)}{0.0014}\,POP^2 + \underset{(0.0856)}{0.2843}\,AREA - \underset{(0.0071)}{0.0068}\,AREA^2 + \underset{(0.8557)}{1.3479}\,\%CITY - \underset{(0.3382)}{0.5604}\,ELEV\text{-}AVG - \underset{(0.6919)}{0.7169}\,ELEV\text{-}SD + \varepsilon^E$$

$$ADOPTION = \underset{(0.1179)}{0.4073}\,ENTRANTS - \underset{(0.0229)}{0.0590}\,BAPLUS - \underset{(0.0292)}{0.0808}\,COMMUTE + \underset{(0.0211)}{0.0599}\,POP + \underset{(0.0192)}{0.0603}\,INCOME + \underset{(0.4406)}{1.9719}\,LARGE\text{-}SC + \underset{(0.4900)}{1.8611}\,SMALL\text{-}SC + \xi^D,$$

for Specification II:

$$ENTRANTS = \underset{(0.0279)}{0.2036}\,POP - \underset{(0.0003)}{0.0018}\,POP^2 + \underset{(0.0890)}{0.0849}\,AREA - \underset{(0.0059)}{0.0016}\,AREA^2 + \underset{(1.0494)}{0.3137}\,\%CITY - \underset{(0.2676)}{0.1770}\,ELEV\text{-}AVG + \underset{(0.7150)}{0.8479}\,ELEV\text{-}SD + \varepsilon^E$$

$$ADOPTION = \underset{(0.1642)}{0.2080}\,ENTRANTS - \underset{(0.0190)}{0.0439}\,BAPLUS - \underset{(0.0330)}{0.0170}\,COMMUTE + \underset{(0.0219)}{0.0607}\,POP + \underset{(0.0152)}{0.0345}\,INCOME + \underset{(0.4496)}{2.4133}\,LARGE\text{-}SC + \underset{(0.4288)}{1.7936}\,SMALL\text{-}SC + \xi^D,$$

and for Specification III:

$$ENTRANTS = \underset{(0.0270)}{0.1577}\,POP - \underset{(0.0003)}{0.0014}\,POP^2 + \underset{(0.0763)}{0.1989}\,AREA - \underset{(0.0059)}{0.0044}\,AREA^2 - \underset{(1.0648)}{0.1411}\,\%CITY - \underset{(0.4236)}{0.1338}\,ELEV\text{-}AVG - \underset{(0.5416)}{0.5159}\,ELEV\text{-}SD + \varepsilon^E$$

$$ADOPTION = \underset{(0.1603)}{0.2601}\,ENTRANTS - \underset{(0.0316)}{0.0515}\,BAPLUS - \underset{(0.0522)}{0.0522}\,COMMUTE + \underset{(0.0198)}{0.0583}\,POP + \underset{(0.0308)}{0.0561}\,INCOME + \underset{(0.5427)}{2.2306}\,LARGE\text{-}SC + \underset{(0.6627)}{1.7848}\,SMALL\text{-}SC + \xi^D.$$

The variables are defined in the footnotes to Tables 4 and 6. The estimated covariances $\{\sigma_{DE}, \sigma_{EP}, \sigma_{DP}\}$ are {0.046,0.138,-0.010} for Specification I and {0.030,0.003,-0.015} for Specification II. The estimated variances $\{\sigma^2_D, \sigma^2_P\}$ are {0.012,0.016} for Specification I and {0.000,0.022} for Specification II.

Table 8: 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 9: Curvature of Incumbents' and Entrants' 1998 Pricing Schedules: FIML Estimation

	Coefficient		Standard Error
Providers' Type of Technology			
Prov_Analog	-0.0444		0.0602
Prov_Mixed	-0.1249	***	0.0353
Entrant	0.0025		0.0269
Plans' Type of Technology			
Plans_Digital	-0.2186	***	0.0461
Market Structure			
Prov_Analog*Competitors	-0.0464	***	0.0117
Prov_Digital*Competitors	-0.0377	***	0.0108
Prov_Mixed* (Plans_Analog)*Competitors	-0.0173		0.0136
Prov_Mixed* (Plans_Digital)*Competitors	-0.0108		0.0127
Demand Characteristics			
Percent with B.A. or more	-0.0002		0.0005
Commuting Time	-0.0013		0.0012
Population	0.0035	**	0.0014
Household Income	0.0020	**	0.0009
Std. deviation, η^{curv}	0.0833	**	0.0431
Log-Likelihood	350.19		
Observations	521		

Selected provider fixed effects included in plan curvature and digital adoption decision equations. Provider-level clustered standard errors based on 50 bootstrapped samples. * = 10% significance, ** = 5% significance, *** = 1% significance. The estimated coefficients of the two auxiliary equations, with the corresponding bootstrap standard errors in parentheses, are:

$$ENTRANTS = \underset{(0.0261)}{0.1503}\,POP - \underset{(0.0003)}{0.0013}\,POP^2 + \underset{(01189)}{0.1804}\,AREA - \underset{(0.0108)}{0.0040}\,AREA^2 - \underset{(0.6676)}{0.0371}\,\%CITY$$
$$- \underset{(0.3197)}{0.4379}\,ELEV\text{-}AVG + \underset{(0.6225)}{0.1059}\,ELEV\text{-}SD + \varepsilon^E$$

$$ADOPTION = \underset{(0.1649)}{0.2340}\,ENTRANTS - \underset{(0.0331)}{0.0388}\,BAPLUS + \underset{(0.0339)}{0.0014}\,COMMUTE + \underset{(0.0208)}{0.0463}\,POP$$
$$+ \underset{(0.0265)}{0.0382}\,INCOME + \underset{(0.3923)}{2.6102}\,LARGE\text{-}SC + \underset{(0.4676)}{1.8296}\,SMALL\text{-}SC + \xi^D.$$

The variables are defined in the footnotes to Tables 4 and 6. The estimated covariances $\{\sigma_{DE}, \sigma_{EP}, \sigma_{DP}\}$ are {0.071,-0.020,-0.034}. The estimated variances $\{\sigma^2_D, \sigma^2_P\}$ are {0.045,0.059}.