

# Uniform vs Competing Standards: A Structural Analysis of the U.S. Wireless Telecommunications Industry\*

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## Abstract

This paper studies how technological compatibility affects network investment and welfare in wireless markets. I develop an empirical model of consumer demand, spatial investment, and pricing using U.S. data from the 3G networks. Counterfactual experiments show that unifying the wireless network under a common standard increases welfare by expanding the effective network through roaming. However, compatibility shifts investment from previously unserved areas toward areas covered by compatible rivals, where firms internalize a larger share of returns. The welfare effects of compatibility depend not only on network size, but also on the spatial allocation of firms' investment responses. (JEL Classification: L13, L15, L96, L51)

The United States and Europe took different approaches to the adoption and regulation of 3G wireless technologies. In the United States, carriers were allowed to deploy competing wireless standards, and the market evolved around two incompatible technologies for 3G: UMTS and CDMA2000. In Europe, by contrast, regulators mandated the development of a common technological standard for 3G networks. These divergent approaches raise a fundamental policy question: should governments mandate a uniform standard when competing firms deploy incompatible technologies? The answer is theoretically ambiguous. Holding technology quality and firms' investment fixed, compatibility can benefit consumers by allowing them to access the combined network of all participating firms and by facilitating roaming across networks. At the same time, compatibility changes firms' incentives to invest. When networks are incompatible, a

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firm's coverage investment primarily attracts consumers away from rivals. Under compatibility, part of the return to investment spills over to compatible rivals, potentially weakening firms' incentives to expand the network. The welfare consequences of standardization therefore depend not only on whether compatibility increases the size of the effective network, but also on how firms respond to the change in investment incentives. This paper provides empirical evidence on these trade-offs by studying the effect of alternative standard-setting policies on coverage investment, prices, profits, and welfare in the U.S. wireless telecommunications industry.

The central insight of the paper is that compatibility changes not only how much firms invest, but also where they invest. Consider a carrier expanding its 3G network. It can invest in an area already covered by a technologically compatible rival, thereby replacing coverage that its customers could access through roaming with its own coverage. I refer to this as catch-up investment. Alternatively, it can expand into an area in which no compatible carrier currently operates. I refer to this as empty-area investment. These two margins have fundamentally different strategic implications under compatibility. Catch-up investment converts roaming coverage into owned coverage without expanding the effective network available to the compatible rival. Empty-area investment, in contrast, expands the network available to the investing firm's customers but simultaneously creates a roaming opportunity for compatible rivals. The investing firm therefore captures only part of the return to empty-area expansion. Technological compatibility consequently changes the geography of investment incentives: firms reallocate investment from expanding the network in empty areas toward converting roaming coverage into owned coverage. Despite this strategic reallocation, compatibility can increase welfare, with the magnitude of the gains depending on demand-side preferences and technology-specific investment costs.

I study these mechanisms in the U.S. wireless market during the 3G era. The market provides a natural setting because the four nationwide carriers operated two incompatible 3G standards: AT&T and T-Mobile deployed UMTS, while Verizon and Sprint deployed CDMA2000. Consumers could obtain roaming coverage from carriers operating the same technology, subject to the roaming agreements governing access across networks, while coverage provided by carriers using the other standard was technologically incompatible. Thus, the effective network available to a subscriber depended on both the coverage of the chosen carrier and the coverage deployed by other carriers using the same standard. At the same time, all carriers made substantial investments in geographic coverage. The geographic location of these investments matters because the return to expanding coverage depends on whether a compatible rival already serves the area. This interaction between compatibility and the spatial allocation of investment is the

focus of the paper.

I develop and estimate a structural model of consumer demand, firms' coverage investment, and national pricing decisions that captures these incentives. On the demand side, consumers choose among carrier–handset bundles and value both the coverage provided by their chosen carrier and the additional coverage available through roaming on a compatible rival. The model also allows consumers to value UMTS and CDMA2000 differently, both through technology-specific quality and through their valuation of roaming coverage. On the supply side, firms choose the amount of coverage investment, with its allocation across catch-up and previously unserved areas determined endogenously by relative marginal profitability. This spatial dimension is important because the return to a unit of investment depends on whether a compatible rival already covers the area: investment in an area already covered by a rival primarily converts roaming coverage into own coverage, whereas investment in an uncovered area expands the network available to both firms.

The empirical challenge is that the data do not reveal this allocation directly. I observe each carrier's total coverage and its change over time, as well as the resulting areas in which carriers have exclusive or overlapping coverage. I do not, however, observe how much of a carrier's investment was made in areas already covered by a compatible rival and how much was made in previously uncovered areas. Moreover, when two compatible carriers invest in previously uncovered areas, their investments may overlap, but the data do not reveal how this overlap arises from their underlying investment decisions. This distinction matters because overlapping empty-area investment does not generate the same roaming spillovers as investment that remains exclusive. I address this problem by modeling the spatial interaction between firms' empty-area investments as a matching process, following the search-and-matching approach of [Buchholz \(2022\)](#). Firms invest in unserved areas but do not perfectly control where their investments meet those of compatible rivals. The probability of overlap depends on the spatial concentration and urban composition of the remaining unserved area. This structure allows me to recover both the allocation of observed investment between catch-up and empty areas and the extent to which empty-area investment becomes overlapping rather than exclusive coverage.

I first estimate consumer demand and the second-stage pricing equilibrium using individual choices and instrumented prices, following the standard approach in the differentiated-products literature ([Berry et al., 1995](#); [Goolsbee and Petrin, 2004](#)). I then estimate the investment stage jointly with the latent allocation of investment and the spatial matching process using Mathematical Programming with Equilibrium Constraints ([Dubé et al., 2012](#); [Su and Judd, 2012](#)). The estimated cost function allows deployment costs to vary with existing infrastructure

and with the underlying wireless technology, while the matching process captures how the spatial characteristics of unserved areas determine the extent to which empty-area investments overlap across compatible networks.

Several results from the structural estimates are important for interpreting the counterfactuals. Consumers have a higher intrinsic valuation for CDMA2000, but they value roaming coverage more strongly when it is provided through UMTS networks. At the same time, the estimated cost of expanding coverage is substantially lower under UMTS than under CDMA2000. Thus, the standard that consumers prefer intrinsically is not the same as the standard that generates the largest compatibility benefit, and the two technologies also differ in the cost of producing additional coverage. These differences imply that the welfare consequences of imposing a common standard depend jointly on demand-side preferences and technology-specific investment costs.

Using the estimated model, I simulate counterfactual equilibria under two alternative standard-setting mandates: a uniform UMTS network and a uniform CDMA2000 network. In each counterfactual, firms re-optimize their coverage investments and prices given the common standard, while the estimated demand and investment parameters remain unchanged, apart from the technology-specific components associated with the mandated standard. The counterfactuals therefore allow firms to respond endogenously to compatibility through both their investment and pricing decisions.

The more novel result is that compatibility changes not only how much firms invest, but also where they invest. Total investment increases under both uniform-standard regimes, but the increase is concentrated in catch-up investment, while investment in previously uncovered areas declines. Under a uniform UMTS standard, for example, mean catch-up investment per market-year rises from 0.013 to 0.049 coverage units, while empty-area investment falls from 0.030 to 0.019. Under a uniform CDMA2000 standard, empty-area investment falls even further by 0.015 percentage points, while catch-up investments increase by 0.016. Compatibility therefore changes the spatial composition of network expansion: firms shift investment toward areas where compatible coverage already exists and away from the network frontier. This spatial response arises because investment in previously uncovered areas generates positive roaming spillovers for compatible rivals, whereas catch-up investment allows firms to convert existing roaming access into their own coverage.

This reallocation also means that the benefits of greater aggregate coverage are not evenly distributed across consumers. Although total coverage increases under both uniform standards, the decline in empty-area investment means that consumers in previously unserved areas re-

ceive less additional coverage than they would absent the reallocation, while consumers in areas already served by a compatible network benefit from the expansion of competing native coverage. Thus, compatibility can increase aggregate investment and coverage while simultaneously shifting the location of network expansion toward consumers who are already served. These spatial investment responses are an important part of the welfare effects of compatibility and would be missed by models that treat network quality as a one-dimensional choice.

### **Contribution to the literature.**

This paper contributes to the literatures on compatibility and network effects, the empirical industrial organization of wireless telecommunications, and structural models of firms' multi-attribute choices.

This paper contributes primarily to the empirical literature on compatibility and network effects. Existing empirical work finds that compatibility can generate substantial welfare gains, largely through increased usage externalities (Ho, 2006; Li, 2017). Most empirical applications, however, focus on vertical compatibility linking complementary products, such as ATM networks (Ishii, 2005), payment networks (Knittel and Stango, 2008), and vertical supply chains (Lee, 2013). Similarly, Li (2017) studies compatibility between complementary goods in the EV-charging market. In these settings, compatibility expands demand but does not generate spatial strategic interactions between horizontally competing networks. I study horizontal compatibility between rival networks that supply the same product and show that its effects operate through the geography of investment. I contribute to this literature by estimating a structural model in which compatibility affects both consumers' effective coverage and firms' returns to geographically differentiated investment. By recovering the latent allocation of investment between catch-up and empty areas, and the extent to which investments by compatible carriers overlap within empty areas, the framework allows me to quantify how compatibility changes both the amount and spatial allocation of investment and, ultimately, welfare.

The paper also contributes to the empirical industrial organization literature on wireless telecommunications. Existing studies typically treat network quality or coverage as exogenous controls in demand estimation (Zhu et al., 2011; Sinkinson, 2014; Macher et al., 2019). More recent work endogenizes quality through network deployment (Sun, 2016; Björkegren, 2019), but generally treats deployment as a scalar quality choice and does not study compatibility-induced investment spillovers. I also differ from Bourreau et al. (2021), which models pricing and entry in a differentiated-product environment but abstracts from compatibility across networks and the resulting investment spillovers. The closest structural approach is Björkegren (2019), who studies the expansion of mobile coverage in a Rwandan quasi-monopoly. In contrast, I study

an oligopoly in which the return to coverage depends on the geography of compatible rivals, allowing compatibility to alter firms’ strategic investment incentives. The framework also allows me to evaluate which technology should be adopted: by recovering consumers’ intrinsic preferences for UMTS and CDMA2000 together with technology-specific deployment costs, I can distinguish between the question of whether compatibility should be mandated and which standard should be selected.

Finally, the paper contributes to the broader structural IO literature on firms’ multi-attribute choices (Fan, 2013; Crawford et al., 2019). While these papers allow firms to adjust quality or product characteristics, I introduce a setting in which the return to a quality investment depends on the location of rivals’ existing quality. The framework recovers an allocation of investment across geographic margins that is not directly observed in the data and allows the possibility of multiple equilibria in the investment game to be addressed directly rather than through an imposed equilibrium-selection rule.

The rest of the paper proceeds as follows. Sections 1 and 2 describe the institutions and data. Section 3 presents stylized facts on coverage, positive spillovers, and strategic investment incentives. Section 4 develops the model of coverage investment, while Section 5 discusses identification. Section 6 describes the parameterization and estimation procedure, and Section 7 presents the estimation results. Section 8 reports the counterfactual analysis, and Section 9 concludes.

## 1 Industry Background

The U.S. wireless telecommunications industry provides a natural setting for studying compatibility, network externalities, and infrastructure investment because carriers operated competing and technologically incompatible standards during the transition from second-generation (2G) to third-generation (3G) mobile networks. Unlike European regulators, who promoted a common GSM standard to facilitate interoperability and roaming, the Federal Communications Commission (FCC) adopted a market-based approach and allowed firms to choose among competing technologies (Gandal et al., 2003; Fuentelsaz et al., 2008). As a result, two technological families emerged in the United States: the GSM family, which evolved into UMTS, and the CDMA family, which evolved into CDMA2000.

A wireless standard defines the protocols through which mobile devices communicate with base stations and core network equipment, including the technologies that enable interoperability and roaming. Although U.S. carriers were interconnected for voice and data communications, roaming compatibility depended largely on the technology deployed. UMTS operators could provide

roaming within the GSM family, while CDMA2000 operators could similarly roam within the CDMA family. Therefore, even though technical solutions enabling roaming across standards were proposed, their implementation required substantial upgrades to network architecture and was rarely adopted (Kim et al., 2003; 3GPP2, 2005). Consequently, coverage provided by a carrier using the same technological family could generate roaming benefits for a rival, whereas coverage provided by a carrier using the other standard generally could not.

During the sample period, the U.S. market was dominated by four nationwide facilities-based carriers: AT&T, T-Mobile, Verizon Wireless, and Sprint. AT&T and T-Mobile followed the GSM-to-UMTS migration path, while Verizon and Sprint adopted CDMA2000. Because these operators followed legacy technology paths, their standard choices were largely determined by historical investments in 2G infrastructure rather than contemporaneous strategic decisions (Saugstrup and Henten, 2006). The resulting configuration provides technologically compatible pairs within an otherwise competitive market.

Wireless service quality is closely tied to network coverage. Mobile communication relies on geographically distributed infrastructure, and carriers can expand coverage through new sites, densification of existing networks, and infrastructure upgrades. Network expansion is costly, and the cost of extending coverage varies across locations because of differences in terrain, population density, site availability, and other local constraints (Funk and Methe, 2001). Thus, coverage is inherently geographic: firms choose where to deploy infrastructure, and the location of investment determines which consumers gain access to the network.

Coverage investments are also linked through roaming agreements. Although carriers primarily provide service through their own infrastructure, subscribers can access a partner's network when their provider's coverage is unavailable. Roaming therefore expands the effective geographic coverage available to consumers without requiring their provider to operate infrastructure in every location. Such arrangements are particularly valuable in areas where low population density makes it uneconomical for multiple carriers to construct overlapping infrastructure.<sup>1</sup> Therefore, the location of existing coverage shapes the interaction between compatible carriers' networks and determines how one carrier's expansion affects its compatible rivals.

Because compatibility across standards remained limited, roaming agreements in the United States developed primarily within technological families. AT&T and T-Mobile established extensive roaming arrangements within the GSM/UMTS ecosystem beginning in the early 2000s,<sup>2</sup> while Sprint and Verizon relied on agreements within the CDMA/CDMA2000 ecosystem.<sup>3</sup> Thus,

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<sup>1</sup>Roaming arrangements were subject to carrier-specific agreements and regulatory requirements. See the FCC's *Reexamination of Roaming Obligations of Commercial Mobile Radio Service Providers* for details.

<sup>2</sup>See [AT&T and T-Mobile agreement](#), [Timeline Roaming Agreement 2011](#).

<sup>3</sup>See the FCC Seventeenth report that can be found at [FCC Reports](#).

coverage provided by a compatible rival could increase the effective coverage available to a carrier’s subscribers, whereas coverage from the other technological family generally could not generate the same roaming benefit. Compatibility therefore links firms’ coverage decisions even when they remain competitors in the product market.

The two technological families also differed in the ease with which consumers could move across networks and providers. SIM-based GSM/UMTS networks allowed relatively easy movement between providers, whereas CDMA2000 networks relied on more carrier-specific handset provisioning, limiting device portability across operators. This asymmetry provides institutional context for the estimated compatibility effects, while the structural model captures compatibility through the roaming component of consumer utility.

## 2 Data

To estimate the model, I construct a comprehensive repeated cross-section database of the U.S. wireless telecommunications industry from 2015 to 2018. Combining multiple sources, the resulting dataset includes detailed information on consumer choices, demographics, carrier pricing, and highly granular spatial network infrastructure. I define a market at the Designated Market Area (DMA) level, which represents a distinct geographic region defined by local television viewing patterns.<sup>4</sup> After filtering, the final estimation sample consists of 145 DMAs. Because the four nationwide wireless providers accounted for over 97.7% of mobile subscribers during the sample period,<sup>5</sup> I restrict the strategic supply-side analysis to these major carriers, aggregating all regional and mobile virtual network operators (MVNOs) into the outside option. Detailed information on the database construction and summary statistics for the final micro and market-level datasets are provided in Appendix A.

Consumer demand and preferences are estimated using the NielsenIQ Consumer Panel dataset,<sup>6</sup> which surveys approximately 40,000 to 60,000 U.S. households annually regarding their mobile carrier choices. The dataset reports the handset-carrier bundle chosen, the quantity of handsets purchased, and the demographics of new subscribers in a given year.

A potential concern is that consumers choose handset-carrier bundles, so carrier choice could partly reflect handset availability rather than network quality. However, this limitation is mitigated by the fact that dominant smartphone operating systems, such as Android and Apple

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<sup>4</sup>For more information on Designated Market Areas, see [Nielsen’s DMA maps](#).

<sup>5</sup>Data source: FCC Eleventh to Eighteenth Mobile Wireless Competition Reports.

<sup>6</sup>Researcher’s own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

iOS, are available across multiple service providers, allowing consumers to pair their preferred device ecosystems with various wireless networks. Therefore, a consumer’s decision to subscribe to one carrier over another is unlikely to be strictly constrained by the type of phone offered in the plan.<sup>7</sup>

To capture preference heterogeneity, I retrieve demographic information, specifically household income brackets, size, and the age of the household head, from the NielsenIQ Panel. To complement this micro-data and ensure representative market sizing, I merge these records with DMA-level population, income, and age distributions sourced from the U.S. Census Bureau and the American Community Survey (ACS) 5-year estimates.

Due to the vast complexity and frequent adjustments of wireless service plans, I rely on the Average Revenue per Reported Unit (ARPU) published annually by the Cellular Telecommunications and Internet Association (CTIA). By annualizing the monthly ARPU, I construct a proxy for the average annual price paid by a consumer for a specific carrier’s service.<sup>8</sup> Because this metric reflects total service revenues divided by active subscribers,<sup>9</sup> it implicitly captures the access fees, data charges, and roaming fees passed on to consumers.

The spatial variables mapping the investment game are constructed from publicly available Federal Communications Commission (FCC) Form 477 data. Providers are required to report their exact network coverage footprints, allowing me to measure the percentage of geographic area covered by each firm’s 2G, 3G and 4G networks at the highly granular census block level. Consistent with the technological compatibility groups of the era, AT&T and T-Mobile operate on the UMTS standard, while Verizon and Sprint operate on the CDMA2000 standard.

By spatially overlaying the coverage maps of compatible rivals, I decompose total DMA coverage into four strategically distinct components: (1) *unique coverage*, where only the focal provider has coverage; (2) *overlap coverage*, where both compatible networks are present; (3) *roaming area*, where only the rival is present and the focal firm can roam; and (4) *empty area*, where neither compatible firm operates. These precise spatial decompositions act as the primary observables identifying the network investment game.

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<sup>7</sup>The AT&T–Apple iPhone exclusivity agreement expired in 2011 and therefore does not affect our 2015–2018 sample, although device-service bundling remained prevalent during this period (Federal Communications Commission, Sixteenth and Seventeenth Reports).

<sup>8</sup>The ARPU is not strictly equal to the average bill for a single household, as an account’s bill may cover multiple devices under a family plan (including phones, tablets, or broadband modems). Rather, it assigns overall service revenue across all revenue-generating devices.

<sup>9</sup>An active unit is defined as a subscriber with an active SIM card.

### 3 Empirical Evidence

In this section, I first present suggestive evidence of the heterogeneity in firms’ strategic coverage investments, which provides the identifying variation for the estimation. I then document several stylized facts that motivate the key features of the model, highlighting the differentiated value of spatial investments. The specifications as well as the detail results are reported in the Online Appendix B.

#### 3.1 Heterogeneity in Spatial Investment Incentives

Firms differ substantially in their patterns of network expansion across and within standards, facing distinct economic trade-offs depending on the geographic target of their investment.

Table 1  
Investment Statistics by Firm

| Firm     | Mean  | Std. Dev. | Min  | Median | Max   | % Positive | N   |
|----------|-------|-----------|------|--------|-------|------------|-----|
| Verizon  | 15.84 | 26.03     | 0.00 | 2.31   | 96.59 | 82%        | 481 |
| AT&T     | 14.38 | 29.56     | 0.00 | 0.00   | 99.93 | 62%        | 391 |
| T-Mobile | 6.56  | 10.87     | 0.00 | 1.60   | 54.93 | 69%        | 265 |
| Sprint   | 7.13  | 12.42     | 0.00 | 1.32   | 87.12 | 74%        | 286 |

*Note:* Investment is measured as the year-on-year percentage point change in 3G coverage. Positive values indicate network expansion. The % Positive column reports the share of market-year observations with positive investment, while  $N$  reports the total number of market-year observations where a positive investment is observed.

Table 1 summarizes the distribution of network investment across firms, measured as the year-over-year percentage-point change in coverage. The share of observations with positive investment ranges from 62% for AT&T to 82% for Verizon. Investment also varies substantially in scale both across and within firms, with some market-year observations involving large expansions and others no expansion at all.

Besides, for each firm, I distinguish two types of locations. Catch-up areas are locations where a compatible rival has coverage but the focal firm does not. Empty areas are locations where neither compatible firm has coverage. This distinction is central because the same amount of network investment can have different strategic implications across the two margins. Investment in a catch-up area converts coverage that the firm’s consumers can already access through roaming into native coverage. Investment in an empty area instead creates new coverage but also generates a potential roaming benefit for the compatible rival.

The empirical question is therefore whether firms respond differently to the availability of these two investment opportunities, and whether these responses vary with the relative position of the two networks.

To document this variation, I estimate block-level Probit and Poisson specifications for the extensive and intensive margins of investment, respectively. The specifications relate firms' investment decisions to the amount of catch-up and empty area available to them and allow these relationships to vary across local markets. Figure 1 summarizes the resulting heterogeneity. The coefficients vary substantially across markets and between investment margins, indicating that firms do not respond uniformly to the geographic opportunities available to them.

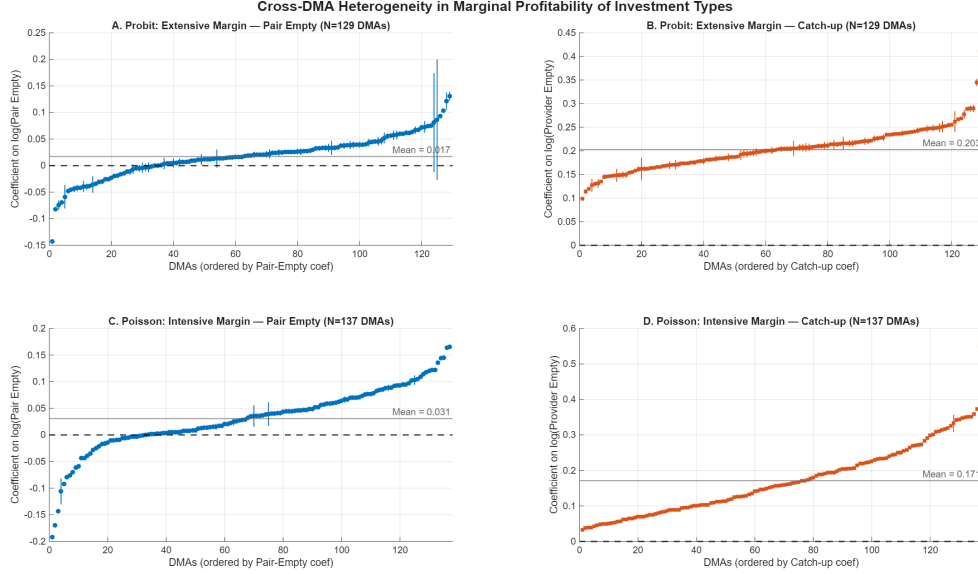


Figure 1  
Heterogeneity in Investment Incentives Across DMAs

*Note:* The figures report DMA-specific coefficient estimates for the available empty-area and catch-up-area investment opportunities. Estimates are shown separately for the extensive (up) and intensive (down).

The data reveal significant variation in how firms respond to empty versus catch-up opportunities, both within and across markets. This divergence suggests that technological differences alone cannot fully explain network deployment patterns; firm-specific incentives and spatial spillovers also play a crucial role. These geographic differences provide the variation that identifies firms' relative returns to catch-up and empty-area investment in the structural model.<sup>10</sup>

### 3.2 Demand Spillovers from Compatibility

A central feature of compatible-network competition is that the effect of a rival's coverage on demand depends on where that coverage is located. When a compatible rival operates in areas not covered by the focal firm, its coverage expands the effective network available to the focal firm's subscribers through roaming, generating a positive demand spillover. Conversely, when

<sup>10</sup>The full empirical specifications, second-stage regressions, and supplementary graphs are detailed in Appendix B..

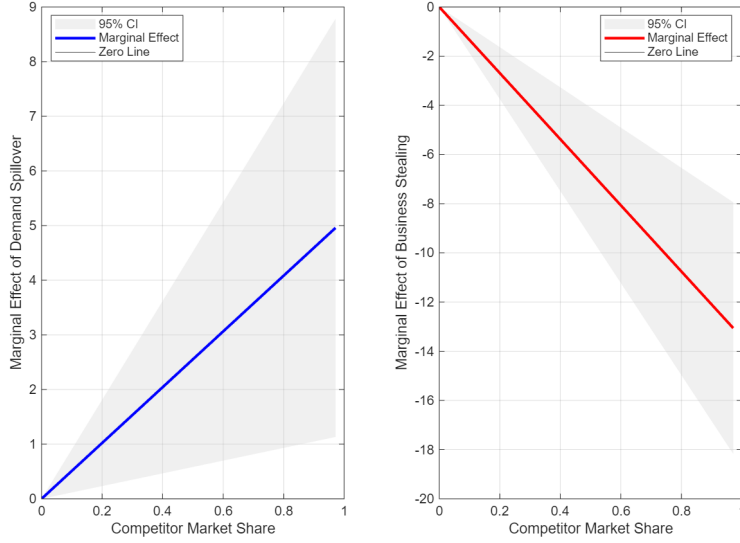


Figure 2  
Demand Spillovers and Business Stealing

*Note:* The figures plot the marginal effect of rival-exclusive coverage (left) and coverage exclusive to the focal firm (right), on the firm's market share.

the focal firm expands coverage in areas where it is the sole provider, the resulting increase in roaming coverage raises the utility of the compatible rival's service and can generate business stealing from the focal firm. I document these two effects in the data by distinguishing coverage exclusive to the rival from coverage exclusive to the focal firm, and examine how variation in these measures affects the focal firm's market share.

Figure 2 shows a clear distinction. A one-standard-deviation increase in rival-exclusive coverage raises the focal firm's market share by 0.898 percentage points, consistent with a positive demand spillover from roaming. In contrast, a one-standard-deviation increase in coverage exclusive to the focal firm reduces the focal firm's market share by 0.480 percentage points, as this coverage enters the rival's utility through roaming and increases competitive pressure. Thus, the effect of a compatible rival's coverage is not determined by its amount alone, but also by its geographic relationship with the focal firm's network.

These patterns provide direct empirical support for the demand structure of the model. Compatibility creates a positive spillover when compatible firms expand into different locations, while coverage in locations served only by the focal firm generates the business-stealing effect through roaming. This geographic distinction motivates the separation between catch-up and empty-area investment in the structural model.<sup>11</sup>

<sup>11</sup>The full empirical specification and additional results are reported in Appendix B.2.

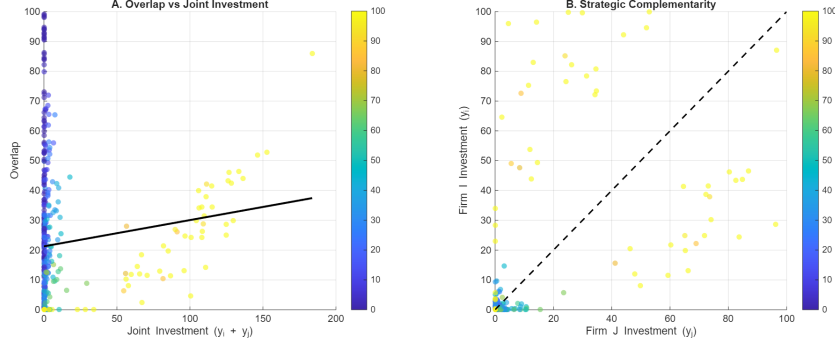


Figure 3  
Determinants of Spatial Overlap

*Note* The figure summarizes the spatial relationships underlying the matching mechanism. Panel A plots overlapping coverage against the sum of the two compatible firms' investments, with observations shaded by the size of the lagged empty area. Panel B plots the investment of one firm against that of its compatible rival. The remaining panels show the relationship between population concentration, urbanization, investment, and overlapping coverage. Spatial HHI and Urban Ratio are computed over the pair-specific empty area in the previous period.

### 3.3 Spatial Matching and Overlap

A final empirical feature concerns overlap in empty areas. When both compatible firms expand into locations that neither previously served, their investments may overlap. I treat this overlap as the outcome of firms independently targeting profitable locations rather than as a separate strategic investment choice. If firms tend to target similar locations because they face correlated local demand conditions, investment by one firm should increase the probability that the other firm's investment lands in the same geographic area.

The evidence supports this spatial matching interpretation. Investment by either compatible firm is positively associated with overlap, while a larger initial empty area reduces overlap, consistent with geographic search frictions. The interaction between changes in the two firms' investments is negative in first differences, consistent with diminishing marginal overlap as both firms expand.

Figure 3 illustrates these matching dynamics. After accounting for the size of the initial empty area, legacy catch-up areas, and joint investment in the empty area, overlap is strongly related to population concentration and urbanization. The Spatial HHI has a positive and significant coefficient ( $\beta = 22.00$ ,  $p < 0.01$ ), as does the Urban Ratio ( $\beta = 11.81$ ,  $p < 0.01$ ). These patterns suggest that investments within empty areas are systematically directed toward locations with more concentrated and urban populations, increasing the likelihood that compatible firms target the same geographic blocks.

The data also reveal that this spatial matching process exhibits diminishing marginal returns. The negative interaction between changes in the two firms' investments indicates that, as both

firms expand simultaneously, additional investment generates progressively less new overlap. These results motivate a concave matching function in which overlap depends on both firms' investment and the size and characteristics of the remaining empty area. Online Appendix B.3 provides the full specifications and additional evidence on the role of population concentration and urbanization.

## 4 The Model

There are  $J$  network providers  $j \in \mathcal{J} = \{1, \dots, J\}$ , each deploying one of two technological standards  $r \in \{UMTS, CDMA2000\}$ . In every period  $t \in \{2015, \dots, 2018\}$ , firms play a two-stage game with simultaneous moves in each stage.

The timing within each period is as follows. At the beginning of period  $t$ , the vector of installed network coverages from the previous period,  $X_{t-1}$ , arrives, and unobserved product quality, demand, and cost shocks become public information. In the first stage, firms simultaneously choose new coverage investments  $Y_t$ , taking as given  $X_{t-1}$  and their expectations about rivals' coverage decisions in period  $t$ . Investments incur firm-specific costs. In the second stage, conditional on the realized coverage vector  $X_t = X_{t-1} + Y_t$ , firms simultaneously set national retail prices in a Bertrand-Nash equilibrium of the product-market subgame and consumers choose among the four providers and the outside option.

Coverage investment is inherently dynamic, but solving a fully dynamic game with the high-dimensional state space of this problem is computationally infeasible. Following standard practice in the network investment literature (Ishii, 2005; Bourreau et al., 2021), I approximate the dynamic problem as a sequence of static equilibria in which firms internalize the forward-looking component of investment through state dependence in the coverage stock  $X_{t-1}$ , without solving an infinite-horizon program. This approximation abstracts from the potential persistence of demand shocks across periods, which would in principle generate additional forward-looking incentives. However, this two-stage game captures the relevant temporal incentives. First, current-period investments increase the firm's current market shares and profits. Second, because installed coverage persistently raises future market shares, firms internalize the continuation value created by the existing coverage vector  $X_{t-1}$ . The two-stage formulation captures the dominant intertemporal channel, state dependence through accumulated coverage, while abstracting from forward-looking responses to anticipated rival deployment. Therefore, the expected-profit function of the two-stage model provides a tractable approximation to firms' dynamic value function while preserving the cross-firm interactions that are key for identification.

## 4.1 Consumer Choice

Following [Berry et al. \(1995\)](#) and [Goolsbee and Petrin \(2004\)](#), I model consumer demand for mobile networks using a random coefficients logit framework. Consumers in a given market choose to subscribe to a network provider  $j \in \mathcal{J}$ , offering deployment standard  $r$ , or the outside option, given existing coverages and prices. The outside option,  $j = 0$ , encompasses other local facilities-based providers.<sup>12</sup> A market is defined as a Designated Market Area (DMA) in a given year, indexed by  $m \in \mathcal{M}$  and  $t \in \{2015, \dots, 2018\}$ . I assume that demand is static and that local markets are independent; a consumer's choice depends exclusively on the coverage and pricing available within their home DMA.<sup>13</sup>

The model specifies an indirect utility function that allows for product differentiation and preference heterogeneity driven by observable consumer demographics and unobservable taste shocks. The indirect utility that consumer  $i$  derives from choosing carrier  $j$  with standard  $r$  in market  $m$  at time  $t$  is:

$$u_{ijrmt} = \delta_{jrmt} + \mu_{ijrmt} + \epsilon_{ijrmt} \quad (1)$$

where  $\delta_{jrmt}$  is the mean utility of the product,  $\mu_{ijrmt}$  is the consumer-specific deviation from  $\delta_{jrmt}$ , and  $\epsilon_{ijrmt}$  is an idiosyncratic taste shock assumed to be drawn from an i.i.d. Type-I Extreme Value distribution. I normalize the mean utility of the outside option such that  $u_{i0mt} = \epsilon_{i0mt}$ .

The individual-specific deviation from the mean utility,  $\mu_{ijrmt}$ , captures variation in consumer preferences over price and coverage as a function of observed demographics and unobserved taste shocks. I specify these heterogeneous preferences as:

$$\begin{aligned} \mu_{ijrmt} = & (\alpha_p d_{imt} + \sigma_p \nu_{ip}) p_{jrt} + (\gamma_z z_{imt} + \sigma_c \nu_{ic}) x_{jrmt}^{3G} + \sigma_{cu} \nu_{icu} x_{jrmt}^{3G} \mathbb{I}_{\{r=UMTS\}} \\ & + \sigma_r \nu_{ir} xRoam_{jrmt}^{3G} + \sigma_{ru} \nu_{iru} xRoam_{jrmt}^{3G} \mathbb{I}_{\{r=UMTS\}} \end{aligned} \quad (2)$$

where  $p_{jrt}$  is the national price,  $d_{imt}$  is a vector of income-group indicators, and  $z_{imt} = (\text{age}_{imt}, \text{hhsz}_{imt})$  includes the consumer's age and household size.<sup>14</sup> The vector  $\alpha_p$  and the coefficients  $\gamma_z$  capture observable demographic shifts in marginal utility: income shifts price sensitivity, while age and household size shift the valuation of own 3G coverage. The parameters

<sup>12</sup>Since the sum of market shares of other wireless providers is not significant compared to the four nationwide providers, I define the choice of other carriers to be included in the outside option. This decision is supported by the fact that the four nationwide network providers have a cumulative market share of 97.7% on average across the United States between 2015 and 2018.

<sup>13</sup>Because the empirical setting observes a repeated cross-section of consumers rather than a panel, and because DMAs are geographically expansive, cross-market network effects and dynamic switching costs are abstracted away to focus on spatial coverage variation.

<sup>14</sup>In estimation, income is discretized into four groups with the lowest group as the omitted base, so  $\alpha_p$  is a vector of three income-group price slopes.

$(\sigma_p, \sigma_c, \sigma_{cu}, \sigma_r, \sigma_{ru})$  govern the dispersion of the unobserved random coefficients on price, own coverage, own coverage interacted with the UMTS standard, roaming coverage, and roaming coverage interacted with the UMTS standard, respectively, with  $\nu_i = (\nu_{ip}, \nu_{ic}, \nu_{icu}, \nu_{ir}, \nu_{iru})' \sim \mathcal{N}(0, I_5)$  representing standard normal taste draws across consumers.

The mean utility component  $\delta_{jrmt}$  absorbs all product attributes that are common across consumers within a given market. This mean utility is decomposed as:

$$\begin{aligned} \delta_{jrmt} = & \bar{\alpha} p_{jrt} + \gamma_{3G} x_{jrmt}^{3G} + \gamma_R xRoam_{jrmt}^{3G} + \gamma_{3G,U} x_{jrmt}^{3G} \mathbb{I}_{\{r=UMTS\}} + \gamma_{R,U} xRoam_{jrmt}^{3G} \mathbb{I}_{\{r=UMTS\}} \\ & + \gamma_{4G} x_{jrmt}^{4G} + \omega_m + \tau_t + \Delta_j + \xi_{jrmt} \end{aligned} \quad (3)$$

where  $\bar{\alpha}$  captures the mean marginal utility for price,  $\gamma_{3G}$  and  $\gamma_R$  are the mean valuations of own 3G coverage and of roaming coverage on same-standard rivals,  $\gamma_{3G,U}$  and  $\gamma_{R,U}$  are the differential valuations of own and roaming coverage for UMTS carriers, and  $\gamma_{4G}$  is the mean valuation of the provider's 4G footprint. The specification includes a rich set of fixed effects:  $\omega_m$  absorbs persistent local demand shocks,  $\Delta_j$  controls for time-invariant national brand unobservables, and  $\tau_t$  accounts for aggregate technological upgrades and macroeconomic shocks, common to all firms and markets. The remaining structural residual,  $\xi_{jrmt}$ , represents the unobserved local quality shock, including the number of subscribers per provider, marketing, and advertising strategies, and the network management.

To study the impact of a single-standard policy on firms' total surplus, and consumers' welfare, I specify a demand model that captures two key features of wireless technology standards. First, standards built on different technologies provide different services to consumers, so consumers may value them differently, and this differential valuation operates through two channels. The overall quality level of each standard is absorbed by the provider fixed effects  $\Delta_j$ : because a carrier's standard is fixed throughout the sample, any constant utility premium of one standard over the other is subsumed in the brand effects and cannot be identified separately from them.<sup>15</sup> What the standard indicator identifies is how the marginal valuation of coverage differs across standards:  $\mathbb{I}_{\{r=UMTS\}}$  enters interacted with own and roaming 3G coverage, so that  $\gamma_{3G,U}$  and  $\gamma_{R,U}$  measure the additional value UMTS subscribers place on native and roaming coverage relative to the CDMA2000 baseline.

Second, within each technological standard, consumers have access not only to the coverage provided by the firm they subscribe to but also to the coverage offered by other firms using

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<sup>15</sup>Equivalently, a standalone standard dummy  $\mathbb{I}_{\{r=UMTS\}}$  entering  $\delta_{jrmt}$  additively would be a linear combination of the provider fixed effects and is therefore omitted.

the same standard, when the chosen provider does not have any. This reflects the presence of roaming agreements among providers that deploy compatible technologies.<sup>16</sup> To capture this feature, I distinguish between a provider's own 3G coverage and the additional coverage available through roaming on same-standard rivals. Specifically, the term  $x_{jrmt}^{3G}$  measures the share of the market area directly covered by firm  $j$ , while  $xRoam_{jrmt}^{3G}$  measures the additional share of area in which service is available through compatible providers in locations where  $j$  lacks coverage.

A consumer therefore assesses the service of provider  $j$  based on the combined network accessible through these two channels. The model incorporates both direct network effects, arising from increases in a provider's own coverage, and indirect network effects, arising from compatibility spillovers generated by same-standard competitors. The corresponding demand parameters capture the valuation of these two components of network quality. When a compatible rival expands its 3G network, the effective coverage available to subscribers of  $j$  increases, even though  $j$  does not itself invest in those locations. These indirect network effects are at the core of compatibility benefits in wireless markets, and they mirror the mechanisms emphasized in [Ishii \(2005\)](#) and [Li \(2017\)](#): the value of a provider's network depends not only on its own investment decisions but also on the investment of same-standard carriers. As a result, the effective quality of a provider's network reflects the jointly determined spatial coverage of the entire compatible cluster, giving rise to demand-side spillovers in coverage investment.

From utility-maximizing behaviour, I obtain the probability that a consumer in market  $m$  at time  $t$  chooses firm  $j$  as the logit choice probability ([McFadden, 1980](#)), which, aggregated over consumers, yields the market share:

$$s_{jrmt}(p_t, X_t, \xi_{mt}; \theta^d) = \int_{\nu} \int_d \frac{\exp(\delta_{jrmt} + \mu_{ijrmt}(x_{jrmt}, p_{jrt}, \nu_i, d_i; \theta^d))}{1 + \sum_{k=1}^J \exp(\delta_{krmt} + \mu_{ikrmt}(x_{krmt}, p_{krt}, \nu_i, d_i; \theta^d))} dF_{\nu}(\nu) dG_d(d) \quad (4)$$

where  $\theta^d$  is the vector of demand parameters to be estimated,  $F_{\nu}(\cdot)$  is the joint distribution of the standard normal taste shifters  $\nu_i$ , and  $G_d(\cdot)$  is the joint distribution of consumer demographics income group, age, and household size.

## 4.2 Supply

The supply side allows firms to compete on prices and network quality by endogenizing both the choice of national prices and the geographic expansion of 3G coverage. I assume that firms have already chosen the technological standard they deploy and that this choice remains fixed

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<sup>16</sup>See Section 1 for institutional details on roaming agreements in mobile telecommunications markets.

over the sample period.

#### 4.2.1 Second Stage Pricing

In every market, the network providers face the demand for their products, pay the marginal costs, and compete on prices to maximize variable profits. I assume that roaming fees paid by a firm to allow consumers to roam on a rival's network are equal to zero, as is the stream of roaming revenues. While this assumption might bias the estimation of compatible positive spillovers, affecting the incentive of firms to invest, it is reasonable given the small percentage of revenues coming from this source.<sup>17</sup>

Each firm is assumed to set a national price to maximize variable profits conditional on its own network and the networks of its rivals:

$$\Pi_{jrt}^{Var}(p_{jrt}, X_{jrt}^{3G}, X_{-j,rt}^{3G}) = \max_{p_{jrt}} \sum_{m \in \mathcal{M}} (p_{jrt} - mc_{jrmt}) s_{jrmt}(p_{jrt}, X_t, \xi_{mt}; \theta^d) MS_{mt}. \quad (5)$$

where  $\Pi_{jrt}^{Var}$  denotes the variable profit,  $MS_{mt}$  is market size,  $p_{jrt}$  is the national-level price,  $X_{jrmt}'$  is the vector of all other relevant variables, and  $mc_{jrmt}$  is the marginal cost. I allow marginal costs to vary across time and DMAs. This assumption allows me to partially account for the complex structure of plans offered by wireless carriers when estimating markups, which in turn determine firms' variable profits. The assumption of national prices is also reasonable as firms do not offer specialized plans or phones by market.<sup>18</sup>

#### 4.2.2 First Stage Investment Choices

Moving back to the first stage, each provider simultaneously chooses its coverage investment given the information available at the beginning of the period and its expectations of its rivals' network choices. I build on the framework of Ishii (2005) and Li (2017) to model firms' investment choices in geographic coverage.

The return to coverage investment depends on where the investment is deployed relative to compatible rivals. A firm can invest in an area that is already covered by at least one same-standard rival, thereby replacing coverage that its customers could access through roaming with its own coverage. I refer to this as catch-up investment. Alternatively, the firm can expand into an area in which no compatible carrier currently operates. I refer to this as empty-area investment.

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<sup>17</sup>In other words, the revenue coming from roaming is unlikely to affect the decision of firms to invest in coverage. See The FCC Annual Mobile Wireless Competition Reports. Ho (2006), and Genakos et al. (2018).

<sup>18</sup>As discussed in the data section, the consumption price encompasses the monthly subscription and usage fees of all component services such as voice calls, mobile data, text messages, and other services. I follow the same modeling choice as in Bourreau et al. (2021).

These two margins have different implications for the firm’s incentives. Catch-up investment converts roaming coverage into own coverage and therefore primarily improves the firm’s competitive position. Empty-area investment expands the effective network available to the firm’s customers, but can also create additional roaming opportunities for compatible rivals. The firm therefore does not necessarily appropriate the full return to empty-area expansion. This geographic structure motivates a distinction between investment in areas where a compatible rival already operates and investment in areas where it does not.

I formalize the coverage expansion at the market level as

$$y_{jmt}^3 = y_{C,jmt} + y_{E,jmt}, \quad y_{C,jmt} \in [0, X_{Roam,jm,t-1}], \quad y_{E,jmt} \in [0, X_{Empty,m,t-1}], \quad (6)$$

where  $y_{jmt}^3$  denotes firm  $j$ ’s total investment in 3G coverage,  $y_{C,jmt}$  denotes investment in areas of market  $m$  already covered by a compatible rival,  $X_{Roam,jm,t-1}$ , and  $y_{E,jmt}$  denotes investment in areas of market  $m$  not covered by any compatible carrier,  $X_{Empty,m,t-1}$ , at the beginning of period  $t$ .

While I observe total investment, the data do not allow me to observe how this investment is allocated across catch-up and empty areas.<sup>19</sup> I therefore allow firms to choose total coverage investment in each market, which is optimally allocated between catch-up and empty-area expansion according to their relative marginal profitability. Notably, the firm chooses the optimal total investment by accounting for the marginal gain of investing in areas already covered by a competitor relative to expanding into uncovered new areas. This formulation captures the firm’s decision over where to deploy a marginal unit of coverage without requiring the econometrician to observe the underlying allocation.

While  $y_{C,jmt}$  does not depend on rivals’ investments,  $y_{E,jmt}$  requires further structure. Investment in the same initially empty area can generate either coverage unique to the firm or overlapping coverage shared with a compatible rival. Note that this partition of  $y_{E,jmt}$  into unique and overlapping coverage is not a direct firm choice but it emerges from the interaction between the firm’s investment and the joint empty-area investments of compatible rivals. This distinction is important because empty-area investment can generate either unique or overlapping coverage.

Following the search-and-matching framework of (Buchholz, 2022), I model this spatial interaction as a market matching process. I define the probability that firm  $j$  covers any given

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<sup>19</sup>While I observe transitions in overlapping and complementarity coverage across periods and markets, these changes depend on both the firm’s own investments and those of its rivals. For example, the change in the roaming coverage of  $j$  entering rivals’ utilities depends on both investments by  $j$  in empty areas, which increases roaming coverage for compatible rivals, and its compatible rivals’ catch-up investment by rivals, which reduces it. The separate components of these changes cannot therefore be recovered directly from the observed data.

point in  $X_{Empty,m,t-1}$  with a unit of  $y_{E,jmt}$  as being drawn from a Poisson process and equal to  $1 - \exp\left(-\frac{y_{E,jmt}}{\alpha_{o,m} X_{Empty,m,t-1}}\right)$ .

Furthermore, for a given number of firms under a compatible network, while the empty area within a market is a common value constant across all firms, the realized overlapping areas are pair-specific. For instance, firm  $j$  might overlap with firm  $k$  in one corner of a market and with firm  $h$  in another. To account for the specific state transitions of overlapping coverages across firm-pairs, I use the following matching function:

$$o_{mjkt} = X_{Empty,m,t-1} \left(1 - e^{-\frac{y_{E,jmt}}{\alpha_{o,m} X_{Empty,m,t-1}}}\right) \times \left(1 - e^{-\frac{y_{E,km t}}{\alpha_{o,m} X_{Empty,m,t-1}}}\right) \quad (7)$$

Equation 7 is a reduced-form representation of spatial matching within the initially empty area. The parameter  $\alpha_{o,m}$  captures the spatial efficiency of network deployment and determines how strongly firms' empty-area investments are concentrated in the same locations. This allows the model to distinguish firms' investment decisions from the spatial realization of those investments. Since firms do not randomly allocate coverage across space, as demonstrated in the stylized facts, I parameterize the spatial search efficiency  $\alpha_{o,m}$  as a function of observable block-level geographic and demographic characteristics of the empty area. To micro-found this spatial crowding, I construct a Spatial concentration Index (HHI) of population across the blocks within market  $m$ 's empty area and define  $UrbanRatio_{m,E}$  as the population-weighted urban share of that area.<sup>20</sup> I specify  $\alpha_{o,m}$  to take an exponential form as follows:

$$\alpha_{o,m} = \exp(\beta_0 + \beta_1 SpatialHHI_{m,E} + \beta_2 UrbanRatio_{m,E}) \quad (8)$$

This specification captures the idea that firms tend to target locations with greater potential profitability. When the unserved population is concentrated in a small number of blocks, compatible firms are more likely to target the same locations, increasing the extent of overlap for a given amount of empty-area investment and, consequently, a low estimated search efficiency ( $\alpha_{o,m}$ ). Similarly, the urban ratio controls for the baseline physical friction of deploying network infrastructure in dense environments versus rural landscapes.<sup>21</sup>

While  $\alpha_{o,m}$  is common across firms within a market, firms ultimately choose asymmetric empty-area allocations ( $y_{E,jmt}$ ), because their marginal returns depend on firm-specific prices, margins,

<sup>20</sup>The formal definition of these two variables can be found in Appendix A.5.

<sup>21</sup>The micro-foundation of the spatial matching mechanism is reported in Appendix C.

and demand.

When expanding their coverage, firms incur costs associated with deploying and maintaining the new network. I assume that investment costs are linear in the amount of new coverage and depend on the technological standard and geographic characteristics of the market:

$$C(y_{jrt}^3; \lambda) = \sum_{m \in \mathcal{M}} \left( \lambda_r + \lambda_{r, \text{urban}} \mathbb{I}_{\{\text{urban}=1\}} + v_{jrmt} \right) y_{jrmt}^3, \quad r \in \{\text{UMTS}, \text{CDMA2000}\}. \quad (9)$$

The standard-specific coefficients  $\lambda_r$  give the per-unit (per-percentage-point) deployment cost of each technology in non-urban markets, and  $\lambda_{r, \text{urban}}$  the additional urban cost, allowing both the baseline and the urban premium to differ across UMTS and CDMA2000. I include  $\lambda_{r, \text{urban}}$  to account for differences in the physical and geographical characteristics of urban and non-urban markets, which may require different investment costs. The shock  $v_{jrmt}$  is firm- and market-specific cost variation observed by the firm but not the econometrician.

In the first stage, firms simultaneously choose the coverage expansion  $y_{jt}^3$  that maximizes expected second-stage profit minus investment costs:

$$\begin{aligned} \pi_{jrt} &= \mathbb{E} \left[ \Pi_{jrt}^{Var}(p_{jrt}, X_{jrt}, X_{-jrt}; \theta^d) \mid I_{jrt-1} \right] - C(y_{jt}^3; \lambda) \\ \text{s.t. } y_{jt}^3 &= y_{C,jt} + y_{E,jt}, \\ 0 &\leq y_{C,jmt} \leq X_{Roam,jm,t-1}, \\ 0 &\leq y_{E,jmt} \leq X_{Empty,m,t-1}, \quad \forall m \in \mathcal{M}. \end{aligned} \quad (10)$$

where  $\Pi_{jrt}^{Var}(\cdot)$  is the second-stage variable profit and  $I_{jrt-1}$  is the firm's information set at the beginning of period  $t$ , which includes the geographic distribution of compatible coverage,  $X_{Roam,jt-1}$ ,  $X_{Roam,-jt-1}$ ,  $X_{Overlap,j,-j \in J_r,t-1}$ , and  $X_{Empty,J_r,t-1}$ , as well as market characteristics such as population density and urbanization.<sup>22</sup>

The realized coverage outcome, however, need not coincide with the equilibrium outcome expected by the firm when the investment is committed. Because coverage realization depends on stochastic spatial search outcomes not known at decision time, realized coverage may depart from anticipated coverage. Following Ishii (2005), I represent this deviation as a mean-zero forecast error:

$$y_{jmt}^3 = y_{E,jmt}^* + y_{C,jmt}^* + e_{jmt}, \quad \mathbb{E}[e_{jmt} \mid I_{jrt-1}] = 0, \quad (11)$$

where  $(y_{E,jmt}^*, y_{C,jmt}^*)$  are the equilibrium allocations and  $e_{jmt} = y_{jmt}^3 - \mathbb{E}[y_{jmt}^3 \mid I_{jrt-1}]$  captures

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<sup>22</sup>For details on how these measures are defined see Appendix A.4.

the deviation of realized total coverage from the equilibrium total anticipated by the firm when it makes its investment decision. The error is mean-zero conditional on the firm's information set by construction.

Firms choose total investment taking into account how the marginal unit is allocated between catch-up coverage,  $y_{C,jmt}$ , and expansion into previously uncovered areas,  $y_{E,jmt}$ . Substituting the derivatives of the logit demand system and the spatial matching function into the investment first-order conditions yields

$$\begin{cases} \frac{\partial \pi_{jm}}{\partial y_{C,jmt}} = (p_{jrt} - mc_{jrmt}) \underbrace{s_{jrmt}(1 - s_{jrmt})(\Gamma_{i,3G} - \Gamma_{i,R})}_{\text{gain from replacing roaming with own signal}} \cdot 1 - \frac{\partial C}{\partial y_{jt}} = 0, \\ \frac{\partial \pi_{jm}}{\partial y_{E,jmt}} = (p_{jrt} - mc_{jrmt}) \underbrace{\left[ s_{jrmt}(1 - s_{jrmt})\Gamma_{i,3G} - \sum_{k \neq j \in \mathcal{J}_r} \Gamma_{i,R} s_{jrmt} s_{krmt} e^{-E_{kmt}} \right]}_{\text{gain from unique area} - \text{spillover penalty}} \underbrace{\frac{1}{\alpha_{o,m}} e^{-E_{jmt}}}_{\partial x_{jrmt}^{3G} / \partial y_{E,jmt}} - \frac{\partial C}{\partial y_{jt}} = 0, \end{cases} \quad (12)$$

where  $E_{jmt} = y_{E,jmt} / (\alpha_{o,m} X_{Empty,m,t-1})$ , and  $\Gamma_{i,3G}$  and  $\Gamma_{i,R}$  denote the marginal utilities of own and roaming coverage, respectively. The factor  $e^{-E_{kmt}}$  is the probability that a compatible rival  $k$  has not yet covered the marginal location, so that investment by  $j$  creates coverage that is unique to  $j$  and therefore available to  $k$ 's subscribers through roaming.<sup>23</sup>

The two conditions characterize the firm's optimal allocation of investment across geographic margins. Catch-up investment replaces coverage obtained through a compatible rival with the firm's own coverage. Its marginal return therefore depends on the difference between the value of own and roaming coverage,  $(\Gamma_{i,3G} - \Gamma_{i,R})$ . Because the firm is replacing rather than creating coverage, this margin does not generate an additional coverage benefit for compatible rivals.

Empty-area investment instead creates new own coverage. A marginal unit increases coverage only with probability  $\frac{1}{\alpha_{o,m}} e^{-E_{jmt}}$  because of the spatial matching process. When the resulting coverage remains unique to firm  $j$ , it also becomes accessible to compatible rivals through roaming. This generates the spillover penalty captured by  $\sum_{k \neq j, k \in \mathcal{J}_{*r}} \Gamma_{i,R} s_{jrmt} s_{krmt} e^{-E_{kmt}}$ . The penalty is larger when consumers place greater value on roaming or when compatible rivals have larger market shares. Thus, a larger compatible rival increases the extent to which firm  $j$ 's empty-area investment benefits its competitor and reduces the private return to this investment margin.

Compatibility therefore affects investment incentives through both the value of compatible coverage and the allocation of investment across geographic margins. It raises the value of rivals'

<sup>23</sup>Equation (12) displays the representative-consumer form of the logit share derivatives for transparency.

networks through roaming while reducing the private return to newly created coverage when that coverage can also benefit compatible competitors. The spatial matching process determines the likelihood that this spillover occurs, while the demand system determines its value to consumers and its effect on firms' profits. These mechanisms generate the strategic investment responses that drive the counterfactual analysis.

**Equilibrium.** A Subgame Perfect Nash Equilibrium consists of investment choices and prices  $(y^3, p(X))$  that constitute a Nash equilibrium in every subgame. Rather than imposing equilibrium existence and uniqueness, I verify them computationally. The solution algorithm searches for and certifies pure-strategy equilibria market-by-market and period-by-period. Following Jia (2008), I assess the implications of potential multiplicity by considering the two extreme equilibria, which provide bounds on equilibrium outcomes. In the empirical application, these bounds coincide in every market-period for which a pure-strategy equilibrium is verified (Appendix G).

## 5 Identification

This section discusses the identification of the vector of demand parameters  $(\theta^d, \xi_{jrm})$  and the supply-side parameters and variables  $(mc_{jrm}, \lambda, v, \alpha_{o,m}(\beta), y_E, y_C)$ .

### 5.1 Identification of the demand and second-stage supply parameters

To identify the demand parameters  $\theta^d$  and the unobserved market quality  $\xi_{jrm}$ , I build on the strategies of Goolsbee and Petrin (2004) and Bourreau et al. (2021).

The nonlinear taste parameters are identified from the micro-data. Specifically, leveraging the NielsenIQ demographic data as in Bourreau et al. (2021), the observed heterogeneity in price sensitivity ( $\alpha_p$ ) is identified by the interaction between household income and the national price. As the choice probabilities of high-income versus low-income households shift in response to the same national price, the model pins down these demographic coefficients. The same logic holds for the household size and age coefficients ( $\gamma_z$ ).

However, if the omitted attributes of the products included in  $\xi_{jrm}$  are correlated with prices, ignoring this correlation will bias the heterogeneous price coefficients, making consumers appear less sensitive to prices than they actually are. I deal with this source of correlation following the strategy in Goolsbee and Petrin (2004). In the individual-specific deviation  $\mu_{ijrm}$ , I absorb the full mean utility  $\delta_{jrm}$  using product–market–year fixed effects. Because  $\delta_{jrm}$  captures all product-level endogeneity, the remaining idiosyncratic shock  $\epsilon_{ijrm}$  is independent of price by construction. The nonlinear taste parameters are therefore identified strictly from within-cell

variation in choices across consumers with different demographic characteristics.<sup>24</sup>

Furthermore, because  $\delta_{jrm t}$  absorbs the average market response, the unobserved random coefficients ( $\sigma_p$  and  $\sigma_x$ ) are identified strictly by the residual spread of substitution patterns that cannot be explained by the observed demographic variation.

Having uniquely identified the mean utilities  $\delta_{jrm t}$ , I then can identify the linear preference parameters  $\bar{\alpha}$  and  $(\gamma_{3G}, \gamma_R, \gamma_X)$ . Because prices are set nationally, identification relies on time-series variation in prices across firms combined with cross-market variation in market shares.

The central empirical challenge in the demand side is the mismatch between the national scale of pricing and the local granularity of market shares. Each carrier sets a single national price  $p_{jrt}$  for the firm, market, year triple, while market shares  $s_{jrm t}$ , and therefore the recovered  $\hat{\delta}_{jrm t}$ , vary at the market-year level. Within  $(j, r, t)$  there is no price variation: all cross-market dispersion in  $\hat{\delta}_{jrm t}$  within the triple is necessarily driven by local characteristics  $X_{jrm t}$  or the local structural residual  $\xi_{jrm t}$ . The mean price coefficient  $\bar{\alpha}$  must therefore be identified from between-year variation in  $p_{jrt}$ , of which the panel contains far fewer independent observations than market-year shares. Two consequences follow.

The first consequence is that the national price  $p_{jrt}$  is likely endogenous to the market-level structural error  $\xi_{jrm t}$ . This endogeneity arises through two channels. First,  $\xi_{jrm t}$  subsumes any unobserved brand-time specific quality shocks. For example, a change in national customer service quality by carrier  $j$  in year  $t$  will lead the firm to charge a higher price and simultaneously have higher demand than the price alone would predict, making demand appear less price-sensitive than implied by the price coefficient. Because these  $j, t$ -specific shocks cannot be absorbed by the firm ( $\Delta_j$ ) and year ( $\tau_t$ ) fixed effects without perfectly collinearizing with the national price, they remain in the error term. If a firm adjusts its national price schedule in response to these unobserved national quality shifts,  $p_{jrt}$  will be correlated with  $\xi_{jrm t}$ . Second, because carriers set uniform national prices to maximize aggregate profits, the optimal national price is a strategic function of the entire vector of local demand shocks across all markets. A sufficiently large unobserved local demand shock in heavily weighted markets will induce a shift in the optimal national price, generating a mechanical correlation between  $p_{jrt}$  and the local unobservable.

To ensure that the residual variation is not confounded by national unobserved quality shocks, I employ instrumental variables for price. I assume the structural error  $\xi_{jrm t}$  is mean independent of a vector of exogenous instruments  $Z_{jt}$  that are correlated with price, conditional on the coverage covariates and fixed effects. The identifying variation comes from changes in national

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<sup>24</sup>Berry (1994) shows that such a vector of provider–market–year mean utilities exists and is unique for a broad class of discrete-choice models.

prices across years, net of the brand, market, and year effects, so the panel contains only a handful of independent sources of price variation. This weak identification concerns only the level of the mean price coefficient. The price sensitivity relevant for substitution and the counterfactuals is identified from the demographic price interactions  $\alpha_p$ , which are estimated from individual choices.

The mean coverage preference parameters are identified from spatial cross-sectional variation. Because coverage varies across markets for the same carrier, differences in the recovered  $\delta_{jrm}$  across markets identify the utility value of network density.<sup>25</sup>

Once the mean preference parameters are identified, the unobserved market-level quality  $\hat{\xi}_{jrm}$  is recovered as the structural residual of the model:

$$\hat{\xi}_{jrm} = \hat{\delta}_{jrm} - \hat{\alpha}p_{jrt} - \hat{\gamma}_{3G}x_{jrm}^{3G} - \hat{\gamma}_{RxRoam}x_{jrm}^{3G} - X'_{jrm}\hat{\gamma}_X - \hat{\psi}_m - \hat{\tau}_t - \hat{\Delta}_j \quad (13)$$

By partialling out the fixed effects and the instrumented price effect, the model isolates a market-level  $\hat{\xi}_{jrm}$  that represents the total unobserved state of demand for a carrier in a specific market. While the instrumental variable strategy ensures that the estimated mean price coefficient  $\bar{\alpha}$  is not confounded by unobserved national brand-time quality shocks, these aggregate shocks correctly remain embedded within the recovered structural residual. Intuitively, this process recovers the true, composite unobserved quality, incorporating both the carrier's national momentum and purely local idiosyncratic preferences, by netting out baseline time-invariant brand reputation, average industry trends, and the utility of physical towers. The recovery of market-level unobserved quality  $\xi_{jrm}$  is important because firms observe it as a state variable when choosing coverage in the first-stage investment game.

With the demand system identified, latent marginal costs are recovered through the inversion of the carrier's national optimality conditions. I compute marginal costs through a mark-up inversion following the standard approach in the literature. Because prices in this setting are set nationally and do not vary across markets, while marginal costs may differ across markets, the national pricing first-order condition recovers only a single scalar condition per firm in each period. However, recovering a specific market's marginal cost requires information about marginal costs in all other markets. Because I cannot observe marginal costs at the market level, the system is underdetermined without imposing additional structure.

Rather than imposing arbitrary restrictions on local costs, I invert the national pricing condition

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<sup>25</sup>Following [Sinkinson \(2014\)](#), coverage can be treated as exogenous conditional on the fixed effects, given geographical and topographical constraints. While firms have an incentive to expand their footprint, differences in realized coverage across markets arise from physical constraints that are largely exogenous to the firm, rather than from unobserved local demand shocks.

to recover an average marginal cost,  $\overline{mc}_{jrt}^{(s')}$ :

$$\overline{mc}_{jrt}^{(s')} := \frac{\sum_m MS_{mt} mc_{jrm} \frac{\partial s_{jrm}}{\partial p_{jrt}}}{\sum_m MS_{mt} \frac{\partial s_{jrm}}{\partial p_{jrt}}} = p_{jrt} + \frac{\sum_m MS_{mt} s_{jrm}}{\sum_m MS_{mt} \frac{\partial s_{jrm}}{\partial p_{jrt}}}. \quad (14)$$

Equation (14) identifies the slope-weighted average of market-level marginal costs, where the endogenous weighting scheme is determined by market size ( $MS_{mt}$ ) and the estimated slope of demand in market  $m$  at time  $t$ . This ensures that the recovered mark-ups are fully consistent with the carrier's national pricing strategy and the estimated demand elasticities.

## 5.2 Identification of the investment stage parameters

The main identification challenge in this model is that I observe firms' total investments  $y_{jmt}^3$  and the changes in the spatial coverage states between  $t - 1$  and  $t$ , but I do not observe how firms allocate their investments between catch-up and empty areas, nor do I observe the market-specific spatial friction parameter  $\alpha_{o,m}$ .

To separately identify the latent allocation ( $y_E, y_C$ ) from the observed total investment, I leverage the fundamentally different effects that these two geographic margins have on a firm's marginal profitability. Cross-market variation in the state variables changes both the feasible allocation and the relative marginal returns to the two investment margins, providing the variation needed to recover the latent allocation from the joint system of transition equations and first-order conditions.

I link the latent allocation to the observed evolution of spatial coverage through the changes in overlapping and roaming coverage between  $t - 1$  and  $t$ :

$$\begin{cases} \Delta X_{\text{overlap},m,jkt} = y_{C,j} + y_{C,k} + o_{mjkt} \\ \Delta X_{\text{Roam},mj} = y_{E,k} - y_{C,j} - o_{mjkt} \\ \Delta X_{\text{Roam},mk} = y_{E,j} - y_{C,k} - o_{mjkt} \end{cases} \quad (15)$$

where  $X_{\text{Roam},mj,t}$  denotes coverage provided by firm  $k$  that is accessible to firm  $j$  through roaming, while  $X_{\text{Roam},mk,t}$  denotes coverage provided by firm  $j$  that is accessible to firm  $k$ . The term  $o_{mjkt}$  denotes newly generated overlap from simultaneous investment in previously empty areas. These transitions are combined with the firms' first-order conditions to form the structural system used to recover the latent allocations and the spatial friction

Because the observation error  $e_{jmt}$  defined in the model is mean-zero conditional on the firm's information set, while the structural objects are measurable with respect to it, identification pro-

ceeds through the conditional expectation  $\mathbb{E}[(y^3, \Delta X) \mid \mathcal{I}_{jrt-1}]$ . The observed total investment is the equilibrium outcome of both the overall scale of investment and its internal allocation between catch-up and empty-area effort. Both decisions depend on the state variables in the firm's information set  $\mathcal{I}_{jrt-1}$ , including existing coverage states, rival network configurations, demand primitives, margins, and market shares.

Cross-market heterogeneity in these state variables generates heterogeneity in both the optimal scale and the optimal split. Two markets with the same total investment  $y^3$  can therefore have different empty-area allocations  $y_E$  depending on the relative size of  $X_{Roam}$  and  $X_{Empty}$ , the rival's existing footprint, and the margin structure. This heterogeneity maps into the observed state transitions  $\Delta X$  through the differential effects of  $y_E$  and  $y_C$  on overlapping and unique coverage. The joint system therefore identifies the latent allocations  $(y_{E,j}, y_{E,k})$  and the market-level spatial friction  $\alpha_{o,m}$  from the conditional distribution of  $(y^3, \Delta X)$ .

Intuitively, the observed equilibrium investments, conditional on the spatial state transitions, allow me to infer the underlying value of choice. Because the marginal profitability of each type of investment exhibits significant heterogeneity across markets, the observed outcomes uniquely reveal how firms must have optimally allocated their investments.

To formalize this identification logic, I rely on the following regularity conditions:

**Assumption 1.** *At the true parameter: (i) the market-share functions  $s_{jrm}$  are twice continuously differentiable with respect to coverage, so the structural system is  $C^1$  in the latent parameters. (ii) The marginal utility of own-network coverage weakly dominates roaming:  $\Gamma_{i,3G} > \Gamma_{i,R}$ . (iii) For any total budget  $y_j^3$ ,  $\lim_{y_{C,j} \rightarrow 0} MR_{C,j} > MR_{E,j}(y_j^3)$  and  $\lim_{y_{E,j} \rightarrow 0} MR_{E,j} > MR_{C,j}(y_j^3)$ , so an interior split is optimal whenever both bounds are slack. (iv) The Jacobian of the structural system  $\mathbf{H}$  defined in Appendix D with respect to the latent vector  $(E_{1mt}, E_{2mt}, \alpha_{o,m})$  is nonsingular at the true parameter for each market cell.*

Parts (i)–(iii) are standard regularity and economic-boundary conditions. Part (i) is a property of discrete-choice demand models. Part (ii) enforces basic network-quality differentiation, guaranteeing that the direct demand effect of expanding native coverage outweighs the indirect substitution effect of providing rivals a roaming footprint; it ensures the empty-area marginal revenue is strictly positive so the optimality conditions are well posed. Part (iii) rules out both corner solutions being reached simultaneously: because native coverage offers a strictly superior consumer experience relative to roaming, the marginal revenue of upgrading a populated catch-up area always dominates that of the least-profitable coverage in empty area, and symmetrically at the opposite corner. Part (iv) is the local-identification (rank) condition for the structural

system.<sup>26</sup>

**PROPOSITION 1:** *Under Assumption 1, the search friction parameter  $\alpha_{o,m}$  (and the underlying  $\beta$  coefficients), alongside the latent allocations  $y_E$  and  $y_C$ , are jointly point-identified from the conditional expectation of  $(y^3, \Delta X)$  given the information set.*

Proposition 1 makes clear the role of the firms' optimality conditions in the identification of the latent allocation. The transition equations provide two independent physical restrictions on the three latent objects, the two investment allocations and the spatial friction, because the two unique-coverage transitions differ only by an observed constant and therefore contain the same information. The missing restriction is economic: the first-order conditions respond differently to catch-up and empty-area investment through the business-stealing return to catch-up investment and the rival-spillover effect of empty-area investment. Combining these conditions with the transition equations yields a square system whose Jacobian is nonsingular under Assumption 1(iv). The Implicit Function Theorem then establishes local point identification of the latent allocations and the spatial friction. The formal proof is provided in Appendix D.<sup>27</sup>

The identification of the spatial search friction  $\alpha_{o,m}$  (and its underlying parameters  $\beta$ ) directly exploits exogenous spatial and demographic variation across markets, within-market blocks, and time. The physical constraints of overlapping deployment vary systematically with exogenous variables such as local topography, population density, and urban versus rural classification, which act as exogenous shifters of the empty-area matching efficiency and affect all firms symmetrically. Observing how equilibrium spatial transitions ( $\Delta X$ ) shift across markets with different demographic and geographic profiles therefore uniquely traces out the  $\beta$  parameters. The geographic and demographic characteristics entering  $\alpha_{o,m}$  are predetermined at the block level. Although the composition of the empty area evolves with past investment, the underlying population and urban characteristics of each block are fixed primitives. Conditional on the firm's information set and the observed network state, variation in the composition of the empty area across markets therefore provides the spatial variation used to identify the  $\beta$  coefficients.

**PROPOSITION 2:** *Under Proposition 1, the investment cost parameters  $\lambda$  are point-identified.*

Once Proposition 1 establishes the recovery of the latent budget allocations, the cost parameters follow from the firm's optimality conditions. The key point is that the cost shock  $v_{jrm,t}$  cannot be read off a single first-order condition. Because the cost function is linear in total investment,

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<sup>26</sup>I report that the Jacobian is nonsingular, with a well-behaved condition number, at every estimated cell in Appendix F.9.

<sup>27</sup>I also assess the numerical uniqueness of the estimated solution by re-estimating the model from five different starting values. The estimates of  $\lambda$  are nearly identical across starting values, providing evidence that the empirical solution is not sensitive to the initial conditions. See Appendix F.

the same marginal cost enters both the empty and catch-up margins, so differencing the two optimality conditions cancels  $v_{jrm t}$  entirely and leaves only the split equality  $MR_{E,j} = MR_{C,j}$ . The split equality determines how investment is allocated between the two margins but conveys no information about the level of investment cost, and therefore none about  $v_{jrm t}$ . The cost shock is instead recovered by restoring the level information contained in observed total investment: because a higher cost shock lowers the firm’s optimal scale of deployment, the optimal total is strictly decreasing in  $v_{jrm t}$  and can be inverted to recover it.

With  $v_{jrm t}(\lambda)$  isolated as a function of the parameters, identification proceeds via standard instruments. I assume that, while local investment decisions are endogenous to the realized cost shock, there exist exogenous cost shifters and market characteristics  $\mathbf{Z}_{jrm t}^c$  that are orthogonal to  $v_{jrm t}$ . The cost parameters  $\lambda$  are therefore point-identified by the sample moments  $\mathbb{E}[v_{jrm t}(\lambda) \mid \mathbf{Z}_{jrm t}^c] = 0$ , under the standard rank condition. The full inversion argument is given in Appendix D.

## 6 Estimation

Estimation of the structural model relies on two main methodologies. The demand parameters  $\theta_d$  are estimated in two stages using a random coefficients logit model fit to individual micro data, following [Berry et al. \(1995\)](#) and [Goolsbee and Petrin \(2004\)](#). I then recover markups and market-share-weighted marginal costs from the estimated demand system and observed prices. Finally, the coverage investment cost parameters  $\lambda$  are estimated using a Mathematical Programming with Equilibrium Constraints (MPEC) approach, following [Dubé et al. \(2012\)](#) and [Su and Judd \(2012\)](#). The full estimation routine is detailed in Appendix E.

### 6.1 Demand and 2nd Stage Supply Estimation

I estimate the demand system in two stages. The first stage recovers the nonlinear parameters governing consumer preference heterogeneity, while the second stage decomposes the recovered mean utilities into observable product characteristics and unobserved quality and estimates the corresponding linear parameters by 2SLS.<sup>28</sup>

In the first stage, I estimate the nonlinear parameters  $\theta_2$ , which govern consumer preference heterogeneity, while absorbing the linear component of utility into provider–market–year mean utilities,  $\delta_{jrm t}$ . For a given value of  $\theta_2$ , I recover  $\delta_{jrm t}(\theta_2)$  by equating predicted and observed market shares. Specifically, I solve the Non-Linear Least Squares equation in line with [Goolsbee and Petrin \(2004\)](#):

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<sup>28</sup>Standard errors are computed following the methodology proposed by [citetgoolsbee2004consumer](#).

$$\hat{\delta}_{mt}(\theta_2) = \arg \min_{\delta_{mt}} \sum_j (s_{jmt}(\theta_2, \delta_{mt}) - \hat{s}_{jmt})^2$$

The structural heterogeneity parameters are estimated by maximizing the weighted pseudo log-likelihood of individual household choices:

$$\max_{\theta_2} \mathcal{L}(\theta_2) = \sum_m \sum_{i \in m} w_i \sum_{j \in \mathcal{J}_{mt}} \mathbf{1}\{y_{ijrmt} = 1\} \ln P_{ijrmt}(\theta_2, \hat{\delta}_{mt}(\theta_2))$$

where  $w_i$  denotes the NielsenIQ projection weights, scaling the likelihood to represent the aggregate population,  $P_{ijrmt}$  is the probability that a consumer chooses provider  $j$  in a given market and year, and  $\hat{\delta}_{mt}(\theta_2)$  is the vector of mean utilities that equates predicted and observed shares. In the second stage, the recovered mean utilities  $\hat{\delta}_{jrm}$  are decomposed into observable product attributes, the national price, and the latent local quality shock  $\xi_{jrm}$ . Because national prices may be correlated with unobserved product quality, I estimate the linear parameters by 2SLS, instrumenting for  $p_{jrt}$  with a vector of national-level instruments  $Z_{jt}$  satisfying the moment condition:

$$E[\xi_{jrm} \mid Z_{jt}, x_{jrm}^{3G}, xRoam_{jrm}^{3G}, X'_{jrm}, \psi_m, \tau_t, \Delta_j] = 0$$

I exploit three sources of national-level variation that shift firms' pricing incentives while remaining orthogonal to local demand shocks: spectrum-auction commitments, the staggered retirement of 2G networks, and the composition of the installed handset base.

The first instrument,  $Z_{jt}^{\text{auction}}$ , captures firm-specific capital expenditure shocks from FCC spectrum auctions.<sup>29</sup> Spectrum auctions release blocks of wireless spectrum through a sequential auction process and require winning bidders to commit substantial capital to license payments and network deployment. The timing of these auctions is determined by regulatory and engineering considerations, such as spectrum availability, coordination with incumbent users, and technological readiness, rather than by local demand conditions in any particular DMA. I construct  $Z_{jt}^{\text{auction}}$  as the sum of firm  $j$ 's winning bids across auctions completed in year  $t$  and  $t - 1$ . Because auction timing and outcomes are driven by regulatory schedules and nationwide spectrum strategy rather than local market conditions,  $Z_{jt}^{\text{auction}}$  is plausibly orthogonal to DMA demand shocks  $\xi_{jrm}$ .

The second instrument,  $Z_{jt}^{2G}$ , exploits the staggered timing of 2G network sunseting, constructed as indicator variables for the years in which carrier  $j$  initiated a 2G shutdown. Shutdown timelines were driven by national engineering decisions to refarm spectrum capacity.

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<sup>29</sup>Spectrum auction data are from the Federal Communications Commission (FCC) *Auction Results* databases: the AWS-3 auction (Auction 97) and the Broadcast Incentive Auction (Auction 1000).

Because 2G coverage functions as a legacy backup technology with no direct effect on consumer valuations of 3G service (Appendix F.7), these shutdown schedules isolate national pricing shifts orthogonal to local unobserved quality  $\xi_{jrm t}$ .

The third instrument,  $Z^{\text{device}} * jt$ , uses the lagged national share of non-LTE devices in firm  $j$ 's subscriber base. The composition of a carrier's installed device base affects the aggregate price elasticity of its subscribers and therefore its optimal national markup during the LTE transition. This variation is driven primarily by handset replacement cycles, manufacturer release schedules, and the availability of new network-compatible devices, rather than by demand conditions in individual DMAs. The lagged device composition therefore shifts national pricing while remaining orthogonal to local demand shocks  $\xi_{jrm t}$ .<sup>30</sup>

Given the estimated demand parameters, I recover the implied marginal costs. Due to the constraint of uniform national pricing, the first-order condition dictates that optimal prices equate aggregate marginal revenue to a weighted average of marginal costs across all markets, as specified in Section 5.1.

## 6.2 Supply Estimation

I estimate the investment-cost and spatial-friction parameters  $\Theta = (\lambda, \beta)$  by the generalized method of moments. I implement the estimator as a MPEC, treating the latent equilibrium objects  $(y_E, y_C, o, v, e)$  as optimization variables constrained by the firms' optimality conditions, the matching and transition equations, and the observation equation.

The estimator combines two orthogonality conditions targeting the two parameter blocks. Let  $v_{jrm t}(\Theta)$  denote the cost shock implied by a candidate  $\Theta$ , and let  $c_{mjk t}^B(\Theta) = \Delta X_{mjk t}^{\text{overlap}} - y_{C,j}(\Theta) - y_{C,k}(\Theta) - \hat{o}_{mjk t}(\Theta)$  denote the residual from the overlap-matching relationship. The sample moments are

$$\mathbf{g}(\Theta) = \begin{pmatrix} \frac{1}{N} \sum_{j,r,m,t} v_{jrm t}(\Theta) \mathbf{Z}_{jrm t}^c \\ \frac{1}{N_{\text{pairs}}} \sum_{(j,k),m,t} c_{mjk t}^B(\Theta) \mathbf{W}_{mjk t}^\alpha \end{pmatrix}, \quad \hat{\Theta} = \arg \min_{\Theta, U} \mathbf{g}(\Theta)' W \mathbf{g}(\Theta), \quad (16)$$

where  $U = (y_E, y_C, o, v, e)$  denotes the constrained latent objects. The first block imposes orthogonality between the structural cost shock and the cost instruments  $\mathbf{Z}^c$  which identify  $\lambda$ , while the second imposes orthogonality between the matching residual and the geographic

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<sup>30</sup>Data on 4G LTE device penetration and the share of the U.S. population with access to LTE wireless technologies by provider are from the Federal Communications Commission (FCC), including the *17th Mobile Wireless Competition Report*, the *8th Wireless Competition Report*, and the *2018 Communications Marketplace Report*, together with FCC Form 477 mobile wireless coverage data.

covariates  $\mathbf{W}^\alpha$  entering  $\alpha_{o,m}(\beta)$ . I use a two-step GMM procedure, beginning with a block-diagonal weighting matrix and subsequently updating the weighting matrix for efficiency.

The estimator solves a single constrained problem in which the structural parameters and the latent objects are chosen jointly. For each candidate  $\Theta$ , the firm’s optimality conditions determine the allocation between empty-area and catch-up investment through the equality of their marginal returns, while the level of these returns determines the cost shock  $v_{jrm}$ . The implied total investment  $\hat{y}_{E,jmt} + \hat{y}_{C,jmt}$  then reproduces observed investment up to the mean-zero forecast error  $e_{jmt}$  in (11). The matching function and state transitions link the latent allocations to the observed change in overlap. These equilibrium and matching conditions enter as constraints, and  $\Theta$  minimizes the GMM objective (16) subject to them, so that the cost-shock and matching orthogonality conditions are satisfied jointly with the firm’s optimality conditions. For the cost instruments  $\mathbf{Z}_{jrm}^c$ , I use cross-market variation in legacy 2G infrastructure density, which shifts the marginal cost of upgrading to 3G through co-location economies, together with terrain and urban characteristics that shift construction costs.

Standard errors are computed by a pair-level nonparametric bootstrap that resamples whole compatible pairs, preserving the matching-moment structure.

## 7 Estimation Results

This section discusses the results from the two stages of estimation described in Section 6. Only a small number of key results are reported in the text. Additional results and how well the model fits the data are reported in Appendix F.

### 7.1 Results from the second-stage demand and supply

Table 2 reports the key second-stage results. The demand estimates imply that consumers place substantial value on network coverage. Both own 3G coverage and roaming coverage enter utility positively, with roaming carrying a smaller coefficient than own coverage. The positive interaction between roaming coverage and the UMTS indicator further indicates that the value of roaming is larger for UMTS subscribers. However, consumers prefer the CDMA standards regarding the total coverage of the chosen provider. The estimates also imply substantial heterogeneity in the valuation of coverage, with larger households and, to a lesser extent, older consumers placing greater value on 3G coverage. <sup>31</sup>

The implied marginal costs are tightly clustered across firms, ranging from \$1.68 to \$1.97 per subscriber, with an average markup of \$1.65. The similarity in marginal costs suggests that

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<sup>31</sup>Robustness checks under alternative demand specifications are reported in Appendix F.7.

Table 2  
Demand and Supply Second-Stage Estimates

|                                                            | Coefficient | Standard Error |
|------------------------------------------------------------|-------------|----------------|
| <b>Demand Mean Parameters</b>                              |             |                |
| Price <sup>a</sup>                                         | -1.703      | 2.473          |
| 3G Total Coverage                                          | 23.493      | 5.406          |
| 3G Roaming Coverage                                        | 2.192       | 5.344          |
| 3G Total Coverage $\times$ UMTS                            | -1.056      | 7.848          |
| 3G Roaming Coverage $\times$ UMTS                          | 5.131       | 7.367          |
| 4G Coverage                                                | 7.188       | 3.564          |
| <b>Demand Nonlinear Parameters (<math>\theta_2</math>)</b> |             |                |
| Price $\times$ Income Group 2                              | -0.453      | 0.331          |
| Price $\times$ Income Group 3                              | -0.207      | 0.179          |
| Price $\times$ Income Group 4                              | 0.324       | 0.271          |
| 3G Coverage $\times$ Age                                   | 0.157       | 0.086          |
| 3G Coverage $\times$ Household Size                        | 1.246       | 0.375          |
| $ \sigma_{\text{price}} $                                  | 0.552       | 1.392          |
| $ \sigma_{\text{coverage}} $                               | 5.578       | 1.984          |
| $ \sigma_{\text{coverage} \times \text{UMTS}} $            | 0.279       | 1.364          |
| $ \sigma_{\text{roaming}} $                                | 1.605       | 1.763          |
| $ \sigma_{\text{roaming} \times \text{UMTS}} $             | 0.684       | 2.286          |
| <b>Marginal Costs by Carrier</b>                           |             |                |
| Marginal Cost AT&T                                         | \$1.68      | —              |
| Marginal Cost T-Mobile                                     | \$1.97      | —              |
| Marginal Cost Verizon                                      | \$1.81      | —              |
| Marginal Cost Sprint                                       | \$1.86      | —              |
| Log-likelihood (Phase 1)                                   | -1,414.67   |                |
| Observations                                               | 1,060       |                |
| First-stage $F$                                            | 12,953.1    |                |
| $R^2$ (Phase 2)                                            | 0.524       |                |

<sup>a</sup>Because national prices vary only at the carrier-year level,  $\bar{\alpha}$  is identified from limited between-year variation and is best regarded as weakly instrumented (the first-stage  $F$  computed at the carrier-year level is 8.52). Its point estimate is nonetheless stable across the alternative instrument specifications reported in Appendix F.

*Note:* Firm and DMA-year fixed effects are included in demand; they are reported in the Appendix. Marginal costs and elasticities are derived from the demand estimates combined with the firms' national pricing first-order conditions. Observations are firm-DMA-year cells; the estimation sample spans 4 carriers, 145 DMAs, and 4 years (2015–2018). Standard errors are clustered at the carrier-year level.

differences in pricing and market shares are not primarily driven by cost heterogeneity, but instead reflect differences in network deployment and the spillover structure associated with compatibility. The implied average own-price elasticity is  $-2.28$ , consistent with estimates from the recent telecommunications literature (Sun, 2016; Bourreau et al., 2021).

Table 3  
Mean Quality Elasticities

|          | 1% Change in Network Quality of: |          |         |        |
|----------|----------------------------------|----------|---------|--------|
|          | AT&T                             | T-Mobile | Verizon | Sprint |
| AT&T     | 6.707                            | -0.145   | -4.206  | -1.117 |
| T-Mobile | -1.067                           | 2.065    | -2.596  | -1.277 |
| Verizon  | -3.826                           | -0.193   | 6.098   | -1.148 |
| Sprint   | -3.149                           | -0.510   | -3.836  | 6.288  |

*Note:* Entries are mean individual elasticities. Diagonal elements are own-coverage elasticities; off-diagonal element  $(j, k)$  is the percent change in firm  $j$ 's market share from a 1% increase in firm  $k$ 's coverage. Values are averaged across consumers and market-years. Carriers are grouped by standard: AT&T and T-Mobile (UMTS), Verizon and Sprint (CDMA2000).

Table 3 summarizes the implied coverage elasticities. Own-coverage elasticities are positive and economically large, ranging from 2.1 for T-Mobile to 6.7 for AT&T. Cross-coverage elasticities are negative, suggesting that network expansion by one carrier reduces rivals' market shares, but the magnitude of this effect is smaller within technology-standard pairs than across standards. This pattern is consistent with the roaming mechanism: when a compatible rival expands, the resulting increase in roaming access partially offsets the competitive loss, whereas expansion by an incompatible rival generates no such benefit.

However, the magnitude of the within-standard spillover differs across the two technologies. The spillover is stronger within the UMTS pair than within the CDMA pair, where Sprint's share remains relatively sensitive to Verizon's coverage. This difference is consistent with the asymmetric device portability and effective roaming possibilities across the two standards discussed in Section 1, which limited the extent to which coverage expansion by a compatible rival translated into an offsetting increase in roaming access.

The estimates reveal two demand-side forces that are central to the counterfactual analysis. Coverage expansion raises the effective quality available to consumers, while compatibility attenuates the competitive effect of a rival's expansion by allowing consumers to access the enlarged compatible network. These forces determine both the value consumers place on a common standard and firms' incentives to invest under alternative compatibility regimes.

Table 4

First-Stage Investment Parameters and Predicted Investment Moments

|                                                                                  | Estimate | Std. Err. |             |             |
|----------------------------------------------------------------------------------|----------|-----------|-------------|-------------|
| <i>Investment Cost Function (<math>\lambda</math>, \$000s per pp per market)</i> |          |           |             |             |
| UMTS, non-urban ( $\lambda_{\text{UMTS}}$ )                                      | 8.19     | 0.71      |             |             |
| UMTS, urban increment ( $\lambda_{\text{UMTS,urban}}$ )                          | 5.32     | 1.06      |             |             |
| CDMA, non-urban ( $\lambda_{\text{CDMA}}$ )                                      | 25.25    | 0.82      |             |             |
| CDMA, urban increment ( $\lambda_{\text{CDMA,urban}}$ )                          | 8.59     | 1.52      |             |             |
| <i>Predicted Investment Moments</i>                                              |          |           |             |             |
|                                                                                  | Mean     | Std. Dev. | 10th Pctile | 90th Pctile |
| Empty-Area Investment ( $\hat{y}_{\text{empty}}$ )                               | 0.030    | 0.096     | 0.000       | 0.063       |
| Catch-Up Investment ( $\hat{y}_{\text{catch.up}}$ )                              | 0.013    | 0.036     | 0.000       | 0.032       |
| Total Investment ( $\hat{y}_{\text{total}}$ )                                    | 0.042    | 0.103     | 0.000       | 0.107       |

*Note:* The upper panel reports the structural cost. Each standard's per-percentage-point coverage cost is reported directly as a non-urban baseline plus an urban increment. Standard errors are percentile bootstrap standard errors. The lower panel reports summary statistics of the latent variables recovered from the structural inversion.

## 7.2 Results from the first-stage

Table 4 reports the key first-stage estimates. The main result is a substantial difference in deployment costs across standards. Increasing coverage by one percentage point costs approximately \$8,200 for UMTS providers and \$25,300 for CDMA2000 providers in non-urban markets, with the corresponding costs in urban markets equal to approximately \$13,500 and \$33,800.

The higher estimated cost of CDMA2000 is consistent with differences in the scale and geographic reach of the two technology ecosystems. UMTS developed on top of the large global GSM installed base and benefited from broad adoption across Europe and Asia, while CDMA2000 was more geographically concentrated, particularly in North America and parts of Asia. Contemporary industry and regulatory accounts also emphasize economies of scale, infrastructure reuse, and equipment availability as important determinants of the cost of 3G deployment.<sup>32</sup> These differences provide a plausible industry basis for the lower marginal deployment cost estimated for UMTS, although they do not by themselves determine the magnitude of the cost difference.

The urban premium is similarly consistent with the economics of network deployment. Expanding coverage in urban markets requires more sites to meet coverage and capacity requirements and faces additional constraints associated with site acquisition, zoning, civil works, and access to existing infrastructure. These considerations provide a natural interpretation for the higher investment cost estimated in urban markets for both standards.<sup>33</sup>

<sup>32</sup>See for instance the International Telecommunication Union, *The Portable Internet*, ITU Internet Reports (2004), and European Commission, Commission Decision of 29 April 2014, Case AT.39939.

<sup>33</sup>A detailed comparison with engineering cost benchmarks is reported in Appendix F.6.

Taken together, the estimates identify the two mechanisms that drive the counterfactual results: compatibility generates positive demand-side roaming benefits while altering firms' strategic returns to network investment, and the two standards differ in their effects on the valuation of coverage and in their deployment costs.<sup>34</sup>

## 8 Counterfactuals

This section uses the estimated model to evaluate the welfare consequences of compatibility in the U.S. wireless industry. I consider two counterfactual regimes: a single UMTS-compatible network and a single CDMA2000-compatible network. In each case, firms re-optimize their coverage and pricing decisions while per-unit coverage investment costs remain fixed at their estimated values. Firms first re-optimize coverage until no profitable unilateral deviation remains and prices are then recomputed at the Bertrand–Nash equilibrium. The counterfactuals therefore allow both the amount and spatial allocation of investment to respond endogenously to compatibility.

The comparison allows me to assess the economic consequences of removing technological fragmentation while holding fixed the legacy technologies available to firms. For incompatible rivals, coverage expansion affects a firm's demand through conventional competitive substitution. Under a common standard, by contrast, coverage built by one firm also becomes available to subscribers of compatible rivals through roaming. Standardization therefore changes both the effective network available to consumers and the strategic return to firms' coverage investments. Table 5 reports the main counterfactual results. Both uniform-standard regimes increase social welfare relative to the multiple-standard equilibrium, but the gains are substantially larger under a uniform UMTS standard. Social welfare net of investment expenditure increases by approximately \$4.44 million under all-UMTS, compared with \$1.57 million under all-CDMA, corresponding to gains of roughly \$1.21 and \$0.54 per person-year, respectively. The welfare effect is therefore positive under either uniform network, regardless of the technology chosen to unify it, but the choice of which technology becomes the common standard is quantitatively important.<sup>35</sup>

The larger gain under UMTS reflects both demand-side and supply-side differences between the

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<sup>34</sup>The model reproduces the main patterns in observed investment across standards and years, including the higher investment intensity of CDMA2000 carriers and the decline in coverage expansion as the 3G rollout matures. Fit statistics and comparisons of observed and predicted moments are reported in Appendix F.10.

<sup>35</sup>Appendix G reports two additional robustness checks. First, I recompute the counterfactuals holding prices fixed to isolate the investment channel. Second, I consider alternative equilibrium-selection rules that favor either dominant or fringe firms whenever multiple equilibria arise. The results are essentially unchanged. Moreover, the estimated counterfactual equilibrium is unique in virtually all market-periods, making the results invariant to the selection rule.

Table 5  
Counterfactual Market Outcomes

|                                                           | Levels   |          |          | Difference vs. Multiple |          |
|-----------------------------------------------------------|----------|----------|----------|-------------------------|----------|
|                                                           | Multiple | All-UMTS | All-CDMA | UMTS                    | CDMA     |
| <i>Social welfare (repriced; model profit units)</i>      |          |          |          |                         |          |
| Consumer surplus                                          | 50438782 | 53718714 | 51050770 | +3279932                | +611988  |
| Producer surplus (variable)                               | 5314560  | 6488542  | 6671273  | +1173982                | +1356713 |
| Investment expenditure                                    | 1160748  | 1174513  | 1562505  | +13765                  | +401757  |
| Social welfare (CS+PS)                                    | 55753342 | 60207255 | 57722043 | +4453913                | +1968701 |
| Social welfare net of investment                          | 54592594 | 59032742 | 56159538 | +4440148                | +1566945 |
| <i>Investment (coverage units; means per market-year)</i> |          |          |          |                         |          |
| $y_{tot}$ mean                                            | 0.0424   | 0.0672   | 0.0434   | +0.0248                 | +0.0010  |
| $y_E$ mean (empty)                                        | 0.0297   | 0.0188   | 0.0149   | -0.0109                 | -0.0148  |
| $y_C$ mean (catch-up)                                     | 0.0127   | 0.0485   | 0.0285   | +0.0357                 | +0.0158  |
| <i>Mean investment per market-year, by carrier</i>        |          |          |          |                         |          |
| AT&T Mobility: $y_E$                                      | 0.0266   | 0.0225   | 0.0234   | -0.0041                 | -0.0031  |
| Sprint: $y_E$                                             | 0.0252   | 0.0117   | 0.0039   | -0.0135                 | -0.0213  |
| T-Mobile: $y_E$                                           | 0.0097   | 0.0082   | 0.0015   | -0.0016                 | -0.0082  |
| Verizon Wireless: $y_E$                                   | 0.0570   | 0.0326   | 0.0308   | -0.0244                 | -0.0263  |
| AT&T Mobility: $y_C$                                      | 0.0001   | 0.0107   | 0.0106   | +0.0106                 | +0.0105  |
| Sprint: $y_C$                                             | 0.0199   | 0.0655   | 0.0375   | +0.0456                 | +0.0176  |
| T-Mobile: $y_C$                                           | 0.0269   | 0.0720   | 0.0294   | +0.0451                 | +0.0025  |
| Verizon Wireless: $y_C$                                   | 0.0040   | 0.0456   | 0.0363   | +0.0416                 | +0.0324  |
| <i>Mean national price, by carrier (repriced)</i>         |          |          |          |                         |          |
| AT&T Mobility                                             | 3.622    | 3.542    | 3.673    | -0.079                  | +0.051   |
| Sprint                                                    | 3.202    | 4.174    | 3.717    | +0.973                  | +0.516   |
| T-Mobile                                                  | 3.351    | 4.366    | 4.092    | +1.015                  | +0.742   |
| Verizon Wireless                                          | 3.763    | 3.984    | 4.375    | +0.222                  | +0.612   |

*Note:* Welfare at the Bertrand–Nash price equilibrium given the counterfactual investment allocation, in model profit units (market-size weighted); consumer surplus is the log-sum measure. Investment in market-area coverage units (one unit = 100 pp); carrier rows are means across that carrier’s market-years.

two technologies. On the demand side, the estimates in Section 7.1 imply that consumers place substantial value on roaming coverage, with the value of roaming higher for UMTS subscribers. A uniform standard therefore generates a larger expansion in effective network quality when the common technology is UMTS. On the supply side, the estimated marginal deployment costs are substantially lower for UMTS. The welfare ranking of the two standards thus reflects the interaction of consumer valuation and deployment costs rather than either mechanism alone. The magnitude of the welfare gains also shows that compatibility affects more than the static value of network access. Firms respond to the change in compatibility by altering both the level and spatial allocation of investment. These endogenous investment responses are central to the quantitative welfare effects of a uniform standard network.

The investment response provides a particularly important mechanism behind the welfare results. Total investment increases under both uniform standards, but the response is much larger under all-UMTS: mean investment rises from 0.0424 to 0.0672 coverage units, compared with 0.0434 under all-CDMA. The increase is concentrated almost entirely in catch-up investment. Under all-UMTS, mean catch-up investment rises from 0.0127 to 0.0485, while empty-area investment falls from 0.0297 to 0.0188. Under all-CDMA, catch-up investment rises to 0.0285, while empty-area investment falls further to 0.0149.

This reallocation follows directly from the roaming spillover created by compatibility. Investment in previously uncovered areas expands the effective network available not only to the investing firm but also to compatible rivals. Each firm therefore captures only part of the return to creating new coverage. By contrast, investment in areas already covered by a compatible rival converts existing roaming access into proprietary coverage, allowing the investing firm to internalize a larger share of the return. Compatibility thus creates a strategic trade-off between expanding the network into new areas and converting existing roaming coverage into owned coverage.

The resulting equilibrium does not imply that compatibility reduces investment. Rather, it changes its composition. Firms invest more overall under a common standard, but they shift investment away from previously uncovered areas and toward catch-up deployment. The contrast is particularly strong under UMTS, where the increase in total investment is driven almost entirely by the expansion of catch-up investment. This distinction is important for understanding the welfare effects of compatibility: the same aggregate increase in physical coverage can generate different consumer and competitive effects depending on where that investment occurs. This investment response contrasts with the standard theoretical prediction that compatibility reduces investment because firms do not fully internalize the spillovers that their coverage

creates for compatible rivals. In the estimated model, however, compatibility also increases the size and value of the effective network available to consumers through roaming, raising the marginal value of additional native coverage. This force more than offsets the loss of private returns from the spillovers to compatible rivals, leading firms to increase total investment while reallocating it toward catch-up deployment.

The response is also heterogeneous across firms. Under the uniform UMTS standard, Sprint and T-Mobile account for most of the additional investment, while AT&T and Verizon expand their networks substantially less. The pattern reflects firms' initial network positions. Carriers with weaker proprietary coverage have more opportunities to convert roaming access into owned coverage once all firms become compatible. Compatibility therefore partly reduces the network-quality advantage associated with historically larger proprietary networks.

The counterfactual results also distinguish the coverage and pricing channels. Allowing firms to re-optimize prices redistributes part of the surplus from consumers to producers, but has only a limited effect on aggregate welfare. Under the all-UMTS counterfactual, consumer surplus increases by approximately \$3.28 million and producer surplus by \$1.17 million, while under all-CDMA the corresponding increases are approximately \$0.61 million and \$1.36 million. The larger producer-surplus gain under CDMA is therefore not sufficient to offset the substantially smaller consumer-surplus gain.

The comparison with the fixed-price counterfactual in Appendix G further shows that the welfare effects are primarily generated by the coverage channel. Holding prices fixed yields welfare gains of approximately \$4.51 million under all-UMTS and \$1.76 million under all-CDMA, very similar to the corresponding gains when prices are allowed to adjust. Endogenous price responses therefore mainly redistribute surplus between consumers and firms rather than generating the underlying efficiency gains. The principal source of the welfare improvement is the change in network coverage induced by compatibility.

Taken together, the counterfactuals reveal two distinct effects of compatibility. First, compatibility raises the effective network available to consumers through roaming, generating a direct demand-side benefit. Second, it changes firms' investment incentives, inducing additional deployment while shifting investment toward catch-up areas. The interaction of these demand and supply responses determines the welfare consequences of standardization and explains why a uniform UMTS standard produces substantially larger gains than a uniform CDMA2000 standard.

The standards considered here were the outcome of technological choices made before the period of observation. By the late 1990s, U.S. carriers had already committed to incompatible

technological paths, and switching standards would have required substantial replacement of network infrastructure. The counterfactuals should therefore be interpreted as evaluating the consequences of imposing compatibility conditional on these legacy technologies, rather than as a model of the original standard-selection process. They capture the effects of standardization given the observed network configurations and estimated deployment technologies; long-run outcomes after subsequent technological generations may differ because they would depend on firms' historical technology and network choices.

## 9 Conclusion

This paper studies how technological compatibility affects firms' incentives to invest in network quality and the resulting welfare consequences in the U.S. wireless industry. I find that compatibility generates substantial welfare gains, but that these gains depend critically on the technology adopted and on firms' investment responses.

The main contribution is to show that compatibility affects not only how much firms invest, but also where they invest. Under a common standard, firms substantially increase catch-up investment in areas already covered by compatible rivals while reducing investment in previously uncovered areas. Compatibility therefore induces a spatial reallocation of network expansion toward areas where firms can internalize a larger share of the returns to investment. As a result, even when aggregate coverage increases, consumers in already-served areas benefit disproportionately, while previously uncovered areas receive less additional investment. These geographic effects would be missed by models that treat network quality as a one-dimensional choice.

These findings suggest that the welfare effects of compatibility extend beyond static price competition and operate through investment incentives and the geography of network expansion. More broadly, the results illustrate how compatibility shapes both market structure and firms' incentives to invest in network quality, providing insights that remain relevant for current debates on interoperability, digital infrastructure, and next-generation communication networks.

## Bibliography

- 3GPP2 (2005): “Interoperability Specification (IOS) for cdma2000 Access Network Interfaces — Part 1 Overview,” .
- BERRY, S., J. LEVINSOHN, AND A. PAKES (1995): “Automobile prices in market equilibrium,” *Econometrica: Journal of the Econometric Society*, 841–890.
- BERRY, S. T. (1994): “Estimating discrete-choice models of product differentiation,” *The RAND Journal of Economics*, 242–262.
- BJÖRKEGREN, D. (2019): “The adoption of network goods: Evidence from the spread of mobile phones in Rwanda,” *The Review of Economic Studies*, 86, 1033–1060.
- BOURREAU, M., Y. SUN, AND F. VERBOVEN (2021): “Market entry, fighting brands, and tacit collusion: Evidence from the French mobile telecommunications market,” *American Economic Review*, 111, 3459–3499.
- BUCHHOLZ, N. (2022): “Spatial equilibrium, search frictions, and dynamic efficiency in the taxi industry,” *The Review of Economic Studies*, 89, 556–591.
- CRAWFORD, G. S., O. SHCHERBAKOV, AND M. SHUM (2019): “Quality overprovision in cable television markets,” *American Economic Review*, 109, 956–95.
- DUBÉ, J.-P., J. T. FOX, AND C.-L. SU (2012): “Improving the numerical performance of static and dynamic aggregate discrete choice random coefficients demand estimation,” *Econometrica*, 80, 2231–2267.
- FAN, Y. (2013): “Ownership consolidation and product characteristics: A study of the US daily newspaper market,” *American Economic Review*, 103, 1598–1628.
- FUENTELESZ, L., J. P. MAÍCAS, AND Y. POLO (2008): “The evolution of mobile communications in Europe: The transition from the second to the third generation,” *Telecommunications Policy*, 32, 436–449.
- FUNK, J. L. AND D. T. METHE (2001): “Market-and committee-based mechanisms in the creation and diffusion of global industry standards: the case of mobile communication,” *Research Policy*, 30, 589–610.
- GANDAL, N., D. SALANT, AND L. WAVERMAN (2003): “Standards in wireless telephone networks,” *Telecommunications Policy*, 27, 325–332.

- GENAKOS, C., T. VALLETTI, AND F. VERBOVEN (2018): “Evaluating market consolidation in mobile communications,” *Economic Policy*, 33, 45–100.
- GOOLSBEE, A. AND A. PETRIN (2004): “The consumer gains from direct broadcast satellites and the competition with cable TV,” *Econometrica*, 72, 351–381.
- HO, K. (2006): “The welfare effects of restricted hospital choice in the US medical care market,” *Journal of Applied Econometrics*, 21, 1039–1079.
- ISHII, J. (2005): “Compatibility, competition, and investment in network industries: ATM networks in the banking industry,” *Unpublished working paper*.
- JIA, P. (2008): “What happens when Wal-Mart comes to town: An empirical analysis of the discount retailing industry,” *Econometrica*, 76, 1263–1316.
- KIM, S., H. CHO, H. HAHM, S. LEE, AND M. S. LEE (2003): “Interoperability between UMTS and CDMA2000 Networks,” *IEEE Wireless Communications*, 10, 22–28.
- KNITTEL, C. R. AND V. STANGO (2008): “Incompatibility, product attributes and consumer welfare: evidence from ATMs,” *The BE Journal of Economic Analysis & Policy*, 8.
- LEE, R. S. (2013): “Vertical integration and exclusivity in platform and two-sided markets,” *American Economic Review*, 103, 2960–3000.
- LI, J. (2017): “Compatibility and investment in the us electric vehicle market,” *Job Market Paper*, 23.
- MACHER, J., J. W. MAYO, O. UKHANEVA, AND G. WOROCH (2019): “Demand in a portfolio-choice environment: The evolution of telecommunications,” *Georgetown McDonough School of Business Research Paper*.
- MCFADDEN, D. (1980): “Econometric models for probabilistic choice among products,” *Journal of Business*, S13–S29.
- SAUGSTRUP, D. AND A. HENTEN (2006): “3G Standards: the battle between WCDMA and CDMA2000,” *info*, 8, 10–20.
- SINKINSON, M. (2014): “Pricing and entry incentives with exclusive contracts: Evidence from smartphones,” *Available at SSRN 2391745*.
- SU, C.-L. AND K. L. JUDD (2012): “Constrained optimization approaches to estimation of structural models,” *Econometrica*, 80, 2213–2230.

SUN, P. (2016): “Quality competition in mobile telecommunications: Evidence from Connecticut,” *Available at SSRN 2506340*.

ZHU, T., H. LIU, AND P. K. CHINTAGUNTA (2011): “Wireless Carriers’ Exclusive Handset Arrangements: An Empirical Look at the iPhone,” *Available at SSRN 1962799*.