Endogeneity in Games with Incomplete Information: U.S. Cellphone Service Deployment*

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Abstract

In some discrete games with incomplete information, payoff-relevant states are influenced by unobserved heterogeneity that also directly affects strategic decisions. When ignored, such endogeneity potentially leads to problematic parameter inference and policy implications. We introduce a control-function approach for estimating such games, and apply the method to an entry game of deploying 4G-LTE technology by major U.S. cellphone service providers. Taking network investment as endogenous, we find that a hypothetical T-Mobile and Sprint merger would reduce 4G-LTE deployment across the local markets in our sample, and disproportionately decrease rural coverage. Ignoring such endogeneity would under-predict the negative impacts of the merger, therefore favoring its approval.

Keywords: Endogeneity, Discrete Games with incomplete information, Control Function, Two-Step Nested Pseudo Likelihood, Entry Game, U.S. Cellphone Service.

JEL Classifications: C31; C35; C57; L13; L96.

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1 Introduction

We propose a control-function approach for estimating discrete games with incomplete information (a.k.a. Bayesian games) when observable payoff-relevant covariates are endogenous. Games with incomplete information provide a powerful framework for analyzing strategic interaction among individuals or firms with private information (e.g. types or signals) and have been studied in a wide range of applied contexts. Examples include location choices in video retail industry in Seim (2006); timing of commercials by radio stations in Sweeting (2009); movie release date timing game in Einav (2010); market entry and exit of grocery stores in Grieco (2014); choices of effort by students and teachers in classrooms in Todd and Wolpin (2018); and choices of fitness exercises by adolescents in Jackson, Lin, and Yu (2022). An important assumption required for inference in these empirical studies is that the covariates, at both the player- and the game-level, are exogenous.

When covariates in a game with incomplete information are endogenous, identification and estimation require further assumptions on the joint distribution of covariates and private types. This poses challenges for model inference that are analogous to endogeneity in single-agent qualitative response models but are aggravated in the presence of strategic interaction. More importantly, if such endogeneity is due to unobserved market-level or game-level heterogeneity that also influences the covariates and types of other players, then the private types are generally correlated even after conditioning on all covariates. This complicates the equilibrium characterization, as well as identification and estimation.[1]

Endogeneity in covariates is common in environments with strategic interaction. Berry and Reiss (2007) pointed out that the issues of “endogenous scale of operations" and “endogenous product characteristics in a continuous space" are “empirically important and useful extensions of the existing empirical literature on structural models for market structure."[2] For a specific example, consider the decisions by

[1] To see this, consider a binary game with two players i, j, individual-specific covariates X_i, X_j, and private types u_i, u_j. Suppose that X_i, X_j and u_i, u_j are all correlated through some unknown market-level or game-level factor v_0. In this case, conditioning on (X_i, X_j) is not sufficient for attaining independence between (u_i, u_j) in general. Thus i's equilibrium belief about j's decision D_j would be a non-trivial function of its own types $E(D_j|X_i, X_j, u_i)$.

[2] Dunne, Klimek, Roberts, and Xu (2013) echo this point, stating “... (a direction for future research) involves incorporating firm-level heterogeneity in profits, fixed costs, and/or entry costs that is correlated over time for individual firms." Firm-level covariates that display persistence over time are very likely endogenous.

cellphone service providers to deploy a new generation of cellphone technology in local service markets. These providers rely on cellular network infrastructures, such as transmission facilities and switching offices, to provide cellphone services. As the technology evolved from 3G to 4G-LTE in the last decade, a provider could reconfigure and upgrade its 3G network to deliver 4G-LTE services. In addition, the spillover effects of a provider's 4G-LTE deployment in neighboring markets could reduce the deployment costs in a focal market. Therefore, a provider's 3G deployment in a local market and 4G-LTE deployment in neighboring markets are both important covariates that influence its decision to enter a local 4G-LTE market. Endogeneity in these covariates may result from several sources. For instance, there are unreported demographic or geographic characteristics (e.g., topographic features) that affect both existing 3G deployment and the costs of upgrading facilities for 4G-LTE in a focal market. Besides, a provider's spectrum holdings are not reported in the data, but are strongly (if not perfectly) correlated between focal and neighboring markets. More broadly speaking, endogeneity is a concern in social-economic settings in which payoff-relevant states are influenced by unreported player- or game-level factors. We are not aware of any paper that allows for such flexible sources of endogeneity in empirical analysis of discrete games with incomplete information and investigates the impact on inference and policy implications when endogeneity is ignored. The goal of our paper is to fill this gap.

We contribute to the econometric and empirical literature on discrete games with incomplete information in two ways. First, we introduce a general, feasible control-function method for estimating binary games with incomplete information in the presence of endogenous states. We model endogeneity in covariates through a triangular system that is flexible enough to accommodate correlation through both player-level and game-level unobserved heterogeneity.[3] Specifically, the first (structural, outcome) equation in the system specifies how firm profits are affected by competition and firm-level endogenous states. We model these effects as policy-invariant parameters, and use them to predict market outcomes under counterfactual

[3]Grieco (2014) studies discrete games with exogenous covariates but a flexible information structure that incorporates both game- and individual-level unobserved heterogeneity. In comparison, we use a triangular system to allow for flexible sources of endogeneity in covariates. Marcoux (2022) recovers unobserved heterogeneity of competitors in Canadian telecommunications industry, using the reduced form of their bids for spectrum licenses. He then uses the variation of such heterogeneity to identify incumbents' responses to the new entrant's decisions. In his case, the bids for spectrum licenses do not enter the network investment game directly as payoff-relevant states. In contrast, we construct control functions from endogenous, payoff-relevant states and exogenous instruments.

policy scenarios. The second (auxiliary, selection/endogeneity) equation is reduced-form in nature; it relates the endogenous states directly to profit-relevant exogenous covariates as well as instruments (which affect firm profits only indirectly through the endogenous states).

A notable advantage of this model is that it allows us to identify the effects of competition and endogenous states on market outcomes and to conduct counterfactual policy analysis without having to structurally model another layer of strategic interactions which (pre-)determine the endogenous states. Such advantage exists because of two aspects: (a) the reduced-form endogeneity equation is flexible enough to capture realistic sources of endogeneity, and incorporates instruments for valid inference despite endogeneity; (b) in our policy analysis we consider immediate post-merger scenarios in which the status of the new merger's endogenous states (network deployment) is completely specified. This latter aspect means we do not need post-merger simulation of endogenous states, thus dispensing with the need for a structural module about how endogenous states are pre-determined in a "first-stage" game.

We construct control function variables as residuals from auxiliary regressions using exogenous instruments. (In our application of entry in 4G-LTE markets, we use the lagged demographics of neighboring markets as instruments.) We propose a two-step nested pseudo-likelihood (2SNPL) estimator, and show it is root-n consistent and asymptotically normal. Our Monte Carlo simulation (in Appendix B) shows that the estimator works well in finite samples with moderate sizes.

Heckman (1978), Newey (1987) and Rivers and Vuong (1988) propose methods for dealing with endogenous discrete and continuous covariates in single-agent qualitative response models. While there are other solutions for endogeneity in the literature,[4] the control function approach has proliferated due to its simplicity, flexibility and wide applicability.[5] We contribute to this extensive literature by bringing the control function

[4]Lewbel (2000), Blundell and Powell (2004), Rothe (2009) and Hoderlein (2014) deal with endogeneity in semiparametric binary choice models; Vytlacil and Yildiz (2007) consider nonparametric identification and estimation of average treatment effects of dummy endogenous variables in weakly separable models; Dong and Lewbel (2015) estimate binary choice models with discrete, continuous, or censored endogenous regressors. D'Haultfœuille and Février (2015) and Torgovitsky (2015) show that non-separable models with continuous outcome and endogenous variables can be identified using discrete instruments.

[5]Since its inception by Heckman and Robb (1985), the control function approach has been used in a variety of settings. See, for example, Newey, Powell, and Vella (1999), Chesher (2003), Das, Newey, and Vella (2003), Lee (2007), Florens, Heckman, Meghir, and Vytlacil (2008), Imbens and Newey (2009), Klein and Vella (2010), Petrin and Train (2010), Hahn and Ridder (2011), and Kasy (2011) among others.

approach into a setting of discrete games with incomplete information.[6] We combine control functions with a nested pseudo likelihood method to handle the simultaneity embedded in a game with incomplete information and the endogeneity in regressors at the same time.[7]

Our second contribution is to provide new empirical insights in a setting where endogeneity in firm states affects the inference of competition effect. We apply the 2SNPL estimator to analyze a hypothetical 2016 T-Mobile and Sprint merger on cellphone technology deployment in a selected sample of mostly rural markets.[8] During 2016 and 2018, AT&T, Verizon, T-Mobile and Sprint were the main competitors in the U.S cellphone service industry. They strategically considered whether to enter the remaining scattered markets left open to 4G-LTE deployment. The 4-to-3 merger is clearly a mover-and-shaker event in this industry, which could substantially change firm strategies of entering local markets. Our sample consists of isolated markets that had not deployed the latest generation of cellphone technology at the time. This allows us to focus on the first-order question about the relation between endogenous states and entry decisions on focal markets while abstracting away from tenuous market interdependence. (A full account of such interdependence would require modeling the providers' strategic optimization of deployment on a national level).

Given the scope of our sample, our goal is not to assess the overall merger effect on the industry level. Rather, we aim at providing insights to antitrust and regulatory agencies who care about the possibility that merger exacerbates the urban-rural digital divide. In addition to predicting firm entries in post-merger local markets and the population served, we evaluate the impact of adding a fourth national provider, enabled by a hypothetical government-mandated partial divestiture of assets owned by the merging parties. This is a very meaningful exercise for antitrust and regulatory agencies. For example, while reviewing merger proposals, the Federal Trade Commission (FTC) and the Department of Justice (DOJ) have often mandated

[6]For econometric analyses of static games with incomplete information, see Aradillas-Lopez (2010), Bajari, Hong, Krainer, and Nekipelov (2010), Florens and Sbaï (2010), Tang (2010), De Paula and Tang (2012), Misra (2013), Wan and Xu (2014), Lewbel and Tang (2015), Aradillas-Lopez and Gandhi (2016), Lin and Xu (2017), Xu (2018), Aguirregabiria and Mira (2019), Lin, Tang, and Yu (2021) and Aradillas-López (2020).

[7]The fixed-point algorithm is used to deal with simultaneity of strategic choices in discrete games with incomplete information. See Rust (1987), Aguirregabiria and Mira (2002, 2007) and Kasahara and Shimotsu (2012).

[8]T-Mobile and Sprint proposed a merger deal in 2019 and were approved to merge in 2020 after lengthy legal battles surrounding antitrust concerns. In our simulations, we create a hypothetical merger between these two firms by moving the 2020 merger to the end of 2015.

that the merging firms divest certain assets and facilities to rivaling firms. The goal of such a policy is to strengthen after-merger competition in local markets and to alleviate the loss of consumer welfare due to increased market power of the merged entity.[9] In the case of the 2020 T-Mobile/Sprint merger decision, the DOJ required the merging parties to divest parts of Sprint's prepaid businesses, Sprint's 800 MHz spectrum holding, decommissioned cell sites and retail locations to a potential competitor, DISH Network.

A crucial step in our analysis is to allow for endogeneity in providers' network investment while analyzing their strategic decisions to enter local markets. As noted earlier, two covariates that influence strategic decisions are endogenous (3G deployment in the focal market and 4G-LTE deployment in neighboring markets). Our estimates indicate that unobserved factors in a firm's 4G-LTE deployment decision are negatively correlated with its focal market's 3G deployment and positively correlated with its 4G-LTE deployment in neighboring markets. Both correlations are statistically significant, providing evidence for the endogeneity of these two covariates. These covariates are directly impacted by the merger (the new entity owns a union of network facilities of the merging parties). Thus, any sound analysis of the merger's impact needs to start with a valid, endogeneity-proof inference of covariate effects.

Using our endogeneity-proof estimates, we find that the hypothetical T-Mobile and Sprint merger would substantially reduce the overall 4G-LTE deployment across local markets in our sample, despite the merged firm became a strong competitor and owned better assets after taking over Sprint's cellular networks. This finding counters a typical pro-merger argument that cost synergies lead to wider cellular coverage and benefit consumers.[10] Moreover, our simulations show that the addition of a fourth national firm, mirroring the DOJ's DISH Network merger remedy through divestiture, would not completely offset the merger's negative impact on the population served in our sample. Lastly, we compare the estimation and simulation results with and without taking into account the endogeneity in network investment. This comparison shows that, taking network investment as exogenous, one would over-estimate the total number of entry occurrences but under-estimate the percentage of population

[9] For example, in 2015, the FTC required Albertsons and Safeway to sell 168 stores in 130 local markets as a condition for approving their $9.2 billion merger case.

[10] Our results are consistent with findings in Genakos, Valletti, and Verboven (2018), which used mobile operators' prices and accounting information across 33 OECD countries over a decade to show that both prices and investment per operator increased after a merger and that total industry investment did not change significantly.

under-served under both the merger and the remedy. Ignoring such endogeneity in estimation would, therefore, skew the policy implications for antitrust agencies toward the merger and its proposed remedy.

As our work incorporates endogenous assets in oligopolistic firms' strategic choices, we build on the recent empirical literature in industrial organization that evaluates how merger affects product offerings (Fan, 2013, Wollmann, 2018, Fan and Yang, 2020), quality of service (Elliott, Houngbonon, Ivaldi, and Scott, 2021) and entry (Berry and Waldfogel, 2001, Sweeting, 2010, Li, Mazur, Park, Roberts, Sweeting, and Zhang, 2019, Ciliberto, Murry, and Tamer, 2021, Fan and Yang, 2021). Mergers, in the first place, are consolidations of assets and resources, including production facilities, retail outlets, investments, patents and more. Divestitures are the regulators' responses aimed at counteracting the increased concentration in post-merger assets distribution. Empirical work evaluating the role of divestiture practices in merger cases is scarce, due partly to the lack of data and partly to the lack of a tractable framework to account for the endogeneity of assets and divestiture.[11] To the best of our knowledge, our work is the first to evaluate the role of assets and, more importantly, the role of divestitures in firms' strategic choices using a game-theoretic approach. More broadly, our empirical method provides a very feasible solution to covariate endogeneity in discrete games with incomplete information.

The paper is organized as follows. Section 2 introduces the discrete games with incomplete information and endogenous states and characterizes the Bayesian Nash equilibrium. Section 3 describes the two-step nested pseudo likelihood estimator (2SNPL) and derives its asymptotic properties. Section 4 studies the 4G-LTE entry game of AT&T, Verizon, T-Mobile and Sprint, comparing model estimates and policy implications with and without accounting for endogenous covariates. Section 5 concludes. All proofs, technical details, and robustness checks are rendered in the appendices.

[11] Two recent academic papers provide descriptive evidence on the effects of divestitures: Tenn and Yun (2011) compare pre- and post-divestiture performances of divested brands from the 2008 Johnson & Johnson's acquisition of Pfizer's consumer health division; Soetevent, Haan, and Heijnen (2014) evaluate the effects of the Dutch government's divestiture requirement when allocating rights to operate highway gasoline stations on prices of divested gasoline stations.

2 Incorporating Endogeneity into Discrete Incomplete Information Games

Consider a game of simultaneous discrete choices with private information among K players, indexed by $k \in \mathcal{K} \equiv \{1, 2, ..., K\}$. Each player k is characterized by a $d_x \times 1$ vector of covariates X_k. For each player k, let $X_k \equiv (X_{k1}, X_{k2})$ be partitioned into $d_1 \times 1$ vector of exogenous covariates X_{k1} and $d_2 \times 1$ vector of endogenous covariates X_{k2}. Z_k is $d_z \times 1$ vector of instruments. Each player k observes a private shock $u_k \in \mathbb{R}$, and makes a simultaneous entry decision $Y_k \in \{0, 1\}$ based on the public information $\mathbb{I} \equiv \{X_k, Z_k\}_{k \leq K}$ and the private shock u_k.

A player k's *ex post* payoff for $Y_k = 1$ is

$$X'_{k1}\beta_k + X'_{k2}\gamma_k + \alpha_k \sum_{j \neq k} Y_j + u_k, \tag{1}$$

and that for $Y_k = 0$ is normalized to be zero. Payoff specification similar to Equation (1) is common in the literature of empirical discrete games (see Berry (1992), Seim (2006), and Jia (2008) for examples).[12] The instruments Z_k do not enter the *ex post* payoffs, but contribute to the endogenous variables as follows:

$$X_{k2} = \Pi'_k(X'_{k1}, Z'_k)' + V_k, \tag{2}$$

where Π'_k is a $d_2 \times (d_z + d_1)$ matrix of constant coefficients. Instrument validity requires the coefficients for Z_k in the matrix Π_k to be non-zero. The regressor X_{k2} is endogenous whenever the error terms $V_k \in \mathbb{R}^{d_2}$ and $u_k \in \mathbb{R}$ are correlated.[13]

In any pure-strategy Bayesian Nash equilibrium (psBNE), each player k follows a decision rule $Y_k = 1\{Y^*_k > 0\}$:

$$Y^*_k \equiv X'_{k1}\beta_k + X'_{k2}\gamma_k + \alpha_k \sum_{j \neq k} \mathbb{E}_k(Y_j|\mathbb{I}, u_k) + u_k, \tag{3}$$

where $\mathbb{E}_k(Y_j|\mathbb{I}, u_k)$ is player k's belief about others' decisions, which is consistent with the common prior of $\{u_j\}_{j \leq K}$ and others' strategies in equilibrium. (We can generalize

[12]This tractable functional form is appealing, because it serves as a practical approximation of the expected discounted value of a firm's action. It is infeasible to construct a full-fledged engineering model to investigate the action's effect on a firm's long-run profits. Besides, lack of data on firm-level prices and quantities restricts the researchers' ability to write down a more primitive payoff function.

[13]The linearity in the auxiliary equation (2) is not essential for the method we propose. The control function method applies even when the linear index of (X_{k1}, Z_k) on the right-hand side of equation (2) is replaced by a nonlinear function of (X_{k1}, Z_k), provided the control function variables V_k satisfy Assumption 1. In fact, we use a quadratic functional form with pairwise interactions of all covariates in our application for better fit in the first stage.

by letting the strategic interaction term be a weighted sum of other players' choice probabilities — that is, by allowing the weights $\alpha_{k,j}$ to differ across k as well as j.)

Our method for dealing with endogenous covariates in this model applies under intuitive conditions on the unobserved errors, which are formalized as follows. For each k, let η_k denote the error term in the linear projection of u_k on $\{V_j\}_{j\leq K}$. That is,

$$u_k = \sum_{j\leq K} V_j'\lambda_{k,j} + \eta_k, \tag{4}$$

where $\lambda_{k,j}$'s are coefficients in the linear projection. Basically, u_k absorbs all factors that affect firms' *ex post* payoffs but are not reported in the data. While u_k is the structural private shock for player k in the game, η_k is the "residual private information" after projecting u_k onto the vector of V_j's, which can be recovered from commonly observed variables using Equation (2). In this sense, V's of all firms are effectively public information, as in principle they can be backed out by the econometrician from the auxiliary equation that explains the source of endogeneity.

Assumption 1. *(i)* $\{u_k, V_k\}_{k\leq K}$ *are independent of* $X_1 = \{X_{k1}\}_{k1\leq K}$ *and* $Z = \{Z_k\}_{k\leq K}$ *with zero means. (ii)* $\{\eta_k\}_{k\leq K}$ *are independent of* $\{V_k\}_{k\leq K}$*; and* η_k'*s are independent across the players* $k = 1, 2, ..., K$.

Part (i) of the assumption states the instrument exogeneity; part (ii) posits that the residual private information, from the projection of u_k on the public control variables, are independent between the individual players. Note that Assumption 1 allows the error vectors $\{u_k, V_k\}_{k\leq K}$ to be correlated across players through V_k. This is qualitatively different from single-agent models where observations of individual decision makers are considered independently and identically distributed. Condition (ii) ensures valid control functions can be constructed despite the correlation between different players' private information and the strategic interaction in equilibrium.

It is important to emphasize that this assumption is flexible enough to accommodate different forms of endogeneity in X_{k2}, including those due to player- or game-level unobserved heterogeneity. For example, it allows for existence of information commonly known to the players but not observed by researchers in the sample. Consider a data-generating process whereby V_j is arbitrarily correlated across $j = 1, 2, ..., K$, possibly through some game-level unobserved heterogeneity. Suppose that, for each player k, u_k is a linear combination of $\{V_j\}_{j\leq K}$ and an idiosyncratic noise ϵ_k, with ϵ_k being independent across $k = 1, 2, ..., K$, and jointly independent of $\{X_{j1}, Z_j, V_j\}_{j\leq K}$. Then, for all k, the error term from a linear projection of u_k on $\{V_j\}_{j\leq K}$, denoted as η_k, is identical to ϵ_k. Therefore, the conditions in Assumption 1 are satisfied.

Assumption 1 also accommodates situations in which endogeneity arises because of unreported individual heterogeneity. For example, suppose that there is no unobserved heterogeneity on the game level, and $\{u_k, V_k\}_{k\leq K}$ are independent across all players. For each player k, the vector of individual noises (u_k, V_k') is multivariate normal with non-zero correlation between u_k and the components in V_k due to some unobserved characteristics of player k. Assumption 1 follows from an implication of the multivariate normality. The zero mean restriction in (i) is just a location normalization.

Using Assumption 1, we write the decision rule in (3) as

$$Y_k = 1\{Y_k^* > 0\} = 1\Big\{X_{k1}'\beta_k + X_{k2}'\gamma_k + \alpha_k \sum_{j\neq k} \mathbb{E}_k(Y_j|\mathbb{I}) + \sum_{j\leq K} V_j'\lambda_{k,j} + \eta_k > 0\Big\}. \tag{5}$$

Note that the two conditions in Assumption 1 imply that η_k is independent of $\{X_j, V_j\}_{j\leq K}$ and, consequently, from $\mathbb{I}$. Besides, the independence of η_k across $k = 1, 2, ..., K$ implies that the equilibrium belief $E_k(Y_j|\mathbb{I}, u_k) = E_k(Y_j|\mathbb{I})$, and does not depend on the residual private information $\{\eta_j\}_{j\neq k}$.[14] It is worth noting that, while Assumption 1 is flexible enough to accommodate unobserved heterogeneity on the market/game level, it also ensures that the reduced form in (5) – with the control function variables included – does not involve terms that explicitly condition on such unobserved heterogeneity.

Let F_k and f_k denote the marginal distribution and the density function of η_k, respectively. Thus, we characterize a pure-strategy Bayesian Nash Equilibrium (psBNE) through a vector of conditional choice probabilities (CCPs) $P : \mathbb{I} \mapsto [0, 1]^K$ that solves a fixed-point equation:

$$P = \Gamma(\theta, P), \tag{6}$$

where $\Gamma \equiv (\Gamma_1, ..., \Gamma_K)'$ with

$$\Gamma_k(\theta_k, P) \equiv 1 - F_k\Big(- X_{k1}'\beta_k - X_{k2}'\gamma_k - \alpha_k \sum_{j\neq k} P_j - \sum_{j\leq K} V_j'\lambda_{k,j}\Big), \tag{7}$$

and $\theta \equiv \{\theta_k\}_{k\leq K}$ with $\theta_k \equiv (\gamma_k', \beta_k', \alpha_k', \lambda_k')$. The model admits a *unique* psBNE under the following condition.

Assumption 2. *For each k, $|\alpha_k| < \frac{1}{(K-1)|\sup_t f_k(t)|}$.*

This assumption restricts the strength of interaction between players so that Γ is a contraction mapping and the uniqueness of psBNE is guaranteed. Such uniqueness

[14] To see this, note that conditioning on $\mathbb{I}$ and u_k is equivalent to conditioning on $\{X_k, V_k\}_{k\leq K}$ and η_k, and the claim follows from the independence of η_k across k.

is crucial for counterfactual simulation. Our estimator remains valid under weaker conditions, provided the data is generated from a single equilibrium.[15]

Lemma 1. *Under Assumptions 1 and 2, there exists a unique psBNE.*

Proof. See Appendix A. □

Let P^* denote the profile of conditional choice probabilities in a Bayesian Nash equilibrium. Identification using Equations (6) and (7) requires the usual rank conditions. That is, the support of the vector $(X'_{k1}, X'_{k2}, \sum_{j\neq k} P^*_j, V'_1, \cdots, V'_K)$ is not contained in a linear subspace. Note that this rules out the cases in which the coefficients for Z_k in the matrix Π_k are all zeros. This requires a necessary order condition that there are more instruments in Z_k than endogenous variables in X_{k2}.

By Assumption 1-(i), $\{V_k\}_{k\in\mathcal{K}}$ can be recovered directly as the residuals in the regression of X_{k2} on (X_{k1}, Z_k) in Equation (2), and therefore treated as known covariates for subsequent identification. Aradillas-Lopez (2010) and Bajari, Hong, Krainer, and Nekipelov (2010) provide two distinct sets of conditions under which the players' *ex post* utility functions are identified.

We conclude this section with remarks about extensions of our method. First, note that identification of this model using our control function (CF) approach does not require parametric assumptions on the distribution of η_k. Therefore, for estimation, one can in principle apply the semiparametric estimators in Aradillas-Lopez (2010) to the reduced form in equation (5) by plugging in estimates of V_k. The CF method we propose is more robust than parametric alternatives (which would require fully parametrizing the conditional distribution of u_k given all endogenous covariates X_{k2}). The stochastic restrictions on the unobserved errors we maintain in Assumption 1 are nonparametric, and have direct structural interpretation.

Second, we can extend the CF method to similar games with incomplete information where the endogenous states are discrete rather than continuous. The most intuitive and feasible way to do so is by introducing parametric assumptions (such as multivariate normal) on the joint distribution of (u_k, V_k). In this case the control function variables take the form of the correction terms in Heckman (1978). Recently, Lin and Tang (2022) show how to apply CFs for estimating a social interactions models where

[15]Assumption 2 is similar to the Moderate Social Influence (MSI) condition in the interaction game literature (see Glaeser and Scheinkman, 2003, Horst and Scheinkman, 2006). It is used in the discrete game literature (Brock and Durlauf, 2001, Lee, Li, and Lin, 2014, Lin and Xu, 2017, Xu, 2018, Jackson, Lin, and Yu, 2022, Lin, Tang, and Yu, 2021) for the uniqueness of Bayesian Nash equilibrium.

each member in a group receives an endogenous binary treatment. Gu, Li, Lin, and Tang (2022) also apply similar CFs to identify peer effects in social interactions models with endogenous sample selection. They also generalize the CF method to allow for correlated group fixed effects. With minimal changes, the CF approaches in these papers can be adjusted for use in discrete games with incomplete information.

3 Estimation

Consider a sample of n independent games $i = 1, 2, ..., n$, each involving K players making simultaneous binary decisions. Throughout this section, we use lower-case letters to denote realization of random vectors in the sample. In each game i and for each player k, the sample reports a binary choice $y_{k,i}$, endogenous variables $x_{k2,i}$, and exogenous covariates and instruments $(x_{k1,i}, z_{k,i})$. Let $\mathbb{I}_i = \{x_{k,i}, z_{k,i}\}_{k \leq K}$ denote the information set that is common knowledge shared by all players in a game.

Let Θ and $\mathcal{P} \subseteq [0,1]^{K \times |\mathcal{X}| \times |\mathcal{Z}|}$ denote the parameter spaces for θ and P, respectively, with $\mathcal{X}, \mathcal{Z}$ being marginal support of X_k, Z_k. Let $\theta_0 \in int(\Theta)$ denote the true value of θ in the data-generating process (DGP), and let $P^0 \equiv \{Pr\{Y = y | \mathbb{I} = (x, z)\} : (y, x, z) \in \{0,1\}^K \times \mathcal{X}^K \times \mathcal{Z}^K\}$ denote the actual equilibrium choice probabilities given θ_0 in the DGP.

Assumption 3. *(i) For any $\theta \neq \theta_0$ and $P(\theta)$ that solves $P = \Gamma(\theta, P)$, $P(\theta) \neq P(\theta_0) \equiv P^0$; (ii) common knowledge variables X_i and Z_i have finite supports, denoted as $\mathcal{X}$ and $\mathcal{Z}$; (iii) $(Y_i, X_i, Z_i)_{i=1}^n$ are independent across games, and $Pr\{\mathbb{I}_i = (x, z)\} > 0$ for all $(x, z) \in \mathcal{X}^K \times \mathcal{Z}^K$. (iv) $\eta_{k,i}$ are i.i.d. standard normal.*

Assumption 3(i) is a standard identification condition for estimating games in which the equilibrium is characterized by the solution to a fixed-point problem. See, for example, Assumption 5(C) in Aguirregabiria and Mira (2007) and Assumption 1(e) in Kasahara and Shimotsu (2012). Other papers on asymptotic properties of nested pseudo likelihood estimators in discrete games also assume finite support of states — e.g., Assumption 4 in Aguirregabiria and Mira (2007) and §2.1 in Kasahara and Shimotsu (2012). Assumption 3(iv) adopts a normal parametrization of the distribution of $\eta_{k,i}$. The zero mean of $\eta_{k,i}$ is implied by conditions on (u_k, V_k) in Assumption 1(i); the unit variance of $\eta_{k,i}$ is a necessary scale normalization for estimation.

We propose a two-step nested pseudo likelihood (2SNPL) estimator that builds on a sequential algorithm combining the nested pseudo likelihood estimator in Aguirregabiria and Mira (2007) with the two-stage conditional maximum likelihood in Rivers and Vuong (1988). The *pseudo likelihood* is:

$$L_n(\theta, P; \Pi) = \frac{1}{n}\sum_{i=1}^{n} l_i(\theta, P; \Pi),$$

where $l_i(\theta, P; \Pi) \equiv \sum_{k=1}^{K} log f_{k,i}(\theta, P; \Pi)$, with $\Pi \equiv \{\Pi_k\}_{k\leq K}$ and $f_{k,i}(\theta, P; \Pi)$ defined as

$$Pr\{x'_{k1,i}\beta_k + x'_{k2,i}\gamma_k + \alpha_k \sum_{j\neq k} P_j + \sum_{j\leq K}(x_{j2,i} - \Pi'_j(x'_{j1,i}, z'_{j,i}))'\lambda_{k,j} + \eta_{k,i} > (\leq)0\}$$

if $y_{k,i} = 1$ ($y_{k,i} = 0$). Note that in the definition of $f_{k,i}$, the probability measure relates to the marginal distribution of $\eta_{k,i}$, and (x_k, z_k) are fixed realizations.[16]

With a slight abuse of notation, we let $\Gamma(\theta, P; \Pi)$ denote the mapping $\Gamma(\theta, P)$ as defined in Equation (7) when V_j is replaced by its identifiable counterpart $X_{j2} - \Pi'_j(X'_{j1}, Z'_j)'$. This emphasizes how the mapping depends on the first-stage parameter Π.

Our 2SNPL estimator is defined as follows. In the first stage, regress $x_{k2,i}$ on $(x_{k1,i}, z_{k,i})$ to estimate $\widehat{\Pi}_k$ for each $k \leq K$. In the second stage, plug $\widehat{\Pi} \equiv \{\widehat{\Pi}_k\}_{k\leq K}$ into an iterative algorithm in Aguirregabiria and Mira (2007) to construct a *2SNPL sequence* of estimators as follows:

Step 1. Pick an initial guess $\widehat{P}_0$ for P^0. For example, one can obtain such an initial guess from a reduced-form Probit regression.

Step 2. For each $s \geq 1$, calculate an s-stage estimator for θ as

$$\widehat{\theta}_s = \arg\max_{\theta\in\Theta} L_n(\theta, \widehat{P}_{s-1}; \widehat{\Pi}), \tag{8}$$

and update the choice probabilities recursively as

$$\widehat{P}_s = \Gamma(\widehat{\theta}_s, \widehat{P}_{s-1}; \widehat{\Pi}). \tag{9}$$

If the initial guess $\widehat{P}_0$ is a consistent estimator for the actual P^0 in the DGP, then all elements in the sequence of estimators are consistent for θ_0. This follows from a similar argument for the consistency of two-step pseudo maximum likelihood estimators in Proposition 1 of Aguirregabiria and Mira (2007).

More importantly, there exists a neighborhood around P^0 such that, starting from any initial guess $\widehat{P}^0$ in that neighborhood, the NPL sequence constructed above converges almost surely to a root-n consistent and asymptotically normal (CAN) estimator, which we refer to as a *2SNPL estimator* and characterize in the next paragraph.

[16]The term "pseudo likelihood" is used because the argument P in L_n is a generic profile of choice probabilities, rather than the equilibrium choice probabilities P^0.

Define a *2SNPL operator* associated with the iterations in (8) and (9):

$$\phi_n(P) \equiv \Gamma(\tilde{\theta}_n(P), P; \widehat{\Pi}), \text{ where } \tilde{\theta}_n(P) \equiv \arg\max_{\theta\in\Theta} L_n(\theta, P; \widehat{\Pi}). \tag{10}$$

The set of *2SNPL fixed points* in a sample is defined as $\Lambda_n \equiv \{(\breve{\theta}, \breve{P}) \in \Theta \times \mathcal{P} : \breve{P} = \phi_n(\breve{P}) \text{ and } \breve{\theta} = \tilde{\theta}_n(\breve{P})\}$. If the maximizer $\tilde{\theta}_n(P)$ is unique for any P and $\widehat{\Pi}$ from a given sample, then the mapping $\tilde{\theta}_n$ is continuous by the theorem of maximum. Thus, the 2SNPL operator $\phi_n(\cdot)$ is continuous in the compact and convex set $[0,1]^{K\cdot|\mathcal{X}|\cdot|\mathcal{Z}|} \equiv \mathcal{P}$. It follows from Brouwer's fixed-point theorem that Λ_n is non-empty. We define a *2SNPL estimator* $(\widehat{\theta}_{2SNPL}, \widehat{P}_{2SNPL})$ as the element in Λ_n that leads to the highest value of pseudo likelihood.

3.1 Asymptotic Properties of the 2SNPL Estimator

Let Π_0 denote the true value of Π in the DGP. For simplicity, we also use Π, Π_0 to denote their own vectorization, in which case Π, Π_0 are $K \times d_2 \times (d_1 + d_z)$ vectors. Define the population counterparts of $L_n, \tilde{\theta}_n, \phi_n$ by

$$L_0(\theta, P) \equiv \mathbb{E}\Big[l_i(\theta, P; \Pi_0)\Big];$$

$$\tilde{\theta}_0(P) \equiv \arg\max_{\theta\in\Theta} L_0(\theta, P)\ ;\ \phi_0(P) \equiv \Gamma(\tilde{\theta}_0(P), P; \Pi_0).$$

The set of 2SNPL fixed points in the population is $\Lambda_0 \equiv \{(\theta, P) \in \Theta \times \mathcal{P} : \theta = \tilde{\theta}_0(P) \text{ and } P = \phi_0(P)\}$. Let $s_{\theta,i} \equiv \nabla_\theta l_i(\theta_0, P^0; \Pi_0)$, and define

$$\begin{aligned}
\Omega_{\theta\theta} &\equiv -E\left[\nabla^2_{\theta\theta} l_i(\theta_0, P^0; \Pi_0)\right] = E\left(s_{\theta,i} s'_{\theta,i}\right);\\
\Omega_{\theta P} &\equiv -E\left[\nabla^2_{\theta P} l_i(\theta_0, P^0; \Pi_0)\right] = E\left(s_{\theta,i} s'_{P,i}\right) \text{ where } s_{P,i} \equiv \nabla_P l_i(\theta_0, P^0; \Pi_0);\\
\Omega_{\theta\Pi} &\equiv -E\left[\nabla^2_{\theta\Pi} l_i(\theta_0, P^0; \Pi_0)\right] = E\left(s_{\theta,i} s'_{\Pi,i}\right) \text{ where } s_{\Pi,i} \equiv \nabla_\Pi l_i(\theta_0, P^0; \Pi_0).
\end{aligned}$$

The equalities following the definition above are due to the information matrix equality with regard to the vector of scores. We denote the Jacobian matrices evaluated at the true value $(\theta_0, P^0; \Pi_0)$ as $\Gamma^0_P \equiv \nabla_{P'}\Gamma(\theta_0, P^0; \Pi_0)$, $\Gamma^0_\theta \equiv \nabla_{\theta'}\Gamma(\theta_0, P^0; \Pi_0)$, and $\Gamma^0_\Pi \equiv \nabla_{\Pi'}\Gamma(\theta_0, P^0; \Pi_0)$. Define $M \equiv \Omega_{\theta\theta} + \Omega_{\theta P}(I - \Gamma^0_P)^{-1}\Gamma^0_\theta$. We establish the asymptotic property of $\widehat{\theta}_{2SNPL}$ under the following regularity conditions.

Assumption 4. *(i) Θ is a compact convex subset of a Euclidean space, and $\mathcal{P}$ is a compact convex subset of $(0,1)^{K\cdot|\mathcal{X}|\cdot|\mathcal{Z}|}$; (ii) $E\left[\sup_{\theta,P} |l_i(\theta, P; \Pi_0)|\right] < \infty$. (iii) (θ_0, P^0) is an isolated population NPL fixed point (i.e., it is unique, or else there is an open ball around it that does not contain any other element of Λ_0); (iv) there exists a closed neighborhood of P^0, denoted by $\mathcal{N}(P^0)$, such that, for all P in $\mathcal{N}(P^0)$, $L_0(\theta, P; \Pi_0)$ is globally concave, and its second derivative* *with respect to θ is a nonsingular matrix; (v) the operator $\phi_0(P) - P$ has a nonsingular Jacobian matrix at P^0; (vi) M is nonsingular.*

Recall that $\widehat{\Pi}$ consists of 1st-stage ordinary least squares (OLS) estimates and, therefore, admits a linear, first-order asymptotic representation as

$$\sqrt{n}(\widehat{\Pi} - \Pi_0) = \frac{1}{\sqrt{n}} \sum_{i=1}^{n} r_i(\Pi_0) + o_p(1),$$

where $r_i(\Pi_0) \equiv r_{0,i}$ is the influence function characterizing the limit distribution of the OLS estimator.

Theorem 1. *Under Assumptions 1 to 4, $\hat{\theta}_{2SNPL}$ is a consistent estimator, and*

$$\sqrt{n}(\widehat{\theta}_{2SNPL} - \theta_0) \xrightarrow{d} N\Big(0, M^{-1}E(\tilde{s}_i\tilde{s}_i')\left(M^{-1}\right)'\Big),$$

where

$$\tilde{s}_i \equiv s_{\theta,i} - [\Omega_{\theta P}(I - \Gamma_P^0)^{-1}\Gamma_\Pi^0 + \Omega_{\theta\Pi}]r_{0,i}.$$

Proof. See Appendix A. □

The proof of the theorem amounts to writing down the first-order conditions and the equilibrium constraints that define the 2SNPL estimator, and then using a first-order expansion to account for the impact of the first-stage estimator $\widehat{\Pi}$, as well as the concurrent iteration over conditional choice probabilities.

Similar to Kasahara and Shimotsu (2012), we can establish the following convergence property of the 2SNPL sequence.

Theorem 2. *Suppose that Assumptions 1 to 4 hold and $\Omega_{\theta\theta}$ is nonsingular. There exists a neighborhood $\mathcal{N}$ around P^0 such that, starting from any initial value $\widehat{P}_0 \in \mathcal{N}$, $lim_{s\to\infty}\widehat{P}_s = \widehat{P}_{2SNPL}$ almost surely.*

The contraction mapping property in Lemma 1 implies that $\rho(\Gamma_P^0) < 1$, where $\rho(\cdot)$ is the spectral radius function. The key condition for convergence in Proposition 1 of Kasahara and Shimotsu (2012) holds.[17] With uniform convergence of $L_n(\cdot; \widehat{\Pi})$ to $L_0(\cdot)$ established in the proof of consistency in Theorem 1 (see Appendix A), the proof of Theorem 2 follows from the same steps in Kasahara and Shimotsu (2012) and is, therefore, omitted for brevity.

[17]See Section 2.3 of Kasahara and Shimotsu (2012) for more discussion.

4 Empirical Study: An Entry Game of Cellphone Service Providers

In this section, we illustrate how our method, which takes account of endogenous covariates, provides new insights in policy analyses in a setting where oligopolistic firms compete through strategic 4G-LTE deployment decisions in local markets. We model this deployment decision as an entry game with incomplete information because each firm observes its firm-and-market-specific shocks in the deployment payoff but not necessarily those shocks to its rivals. Other papers using similar information structure for investigating firm entry decisions in different contexts include Seim (2006) and Sweeting (2009). We model the competition between four national cellphone service providers in the U.S.: Verizon Wireless, AT&T Mobility, T-Mobile US and Sprint Corporation (collectively referred to as the "Big Four").[18] The time period we study is from 2015 to 2018, a few years before the proposal of a T-Mobile and Sprint merger in 2019, which eventually went through in early 2020 after lengthy legal battles over antitrust concerns.

In this industry, firms make capital investments in cellular networks and transmission facilities in a specific geographic area before providing services to consumers to that area. Such investments have typically been made in accordance with the dominant technology of the time. For example, throughout most of the 2000s, the third generation of cellphone technology (3G) was the predominant technology, utilizing the 1850 - 1990 MHz spectrum range. Starting from roughly 2010, it was time for the next generation of technology, 4G-LTE.[19] A firm with 3G deployment in a local market can repurpose spectrum used by 3G to support 4G-LTE and can utilize existing facilities, such as cell towers, with upgraded equipment. Such investment also involves some spatial consideration. For example, extending coverage from central Phoenix to nearby cities and towns would be easier than providing *de novo* services to these markets. We measure a potential entrant's network investment for a local market

[18] We will refer to them as Verizon, AT&T, T-Mobile and Sprint henceforth. These cellphone service providers are also known as mobile network operators, wireless service providers, wireless carriers, cellular companies, mobile network carriers, etc. In this paper, we refer to them as firms, providers, and carriers interchangeably.

[19] 4G-LTE stands for the fourth generation, Long Term Evolution. LTE is the technology to deliver 4G standards, defined as having peak upload and download speeds of at least 100 mbps (mega bits per second). 4G-LTE is still not fully 4G, but is considered the closest to 4G standards by international telecommunications communities.

by the firm's 3G deployment in the focal market and 4G-LTE deployment in nearby markets. These two sets of network investments are the firm-specific, endogenous covariates we focus on in our empirical framework. They are important determinants of a firm's decision to provide a new generation of technology in a local market, driven by similar unobserved heterogeneity that underlies a firm's entry decision.

In the following subsections, we describe the background of the U.S. cellphone service industry, the policy relevance of our empirical application, the data we construct, and the empirical specification we use. In particular, we evaluate a counterfactual experiment in which T-Mobile and Sprint merged in 2016, which would have led to different 4G-LTE deployment paths in markets that these firms had not yet entered in 2016. We discuss the discrepancies in policy implications and recommendations with and without accounting for the endogeneity in network investment.

4.1 The U.S. Cellphone Service Industry at a Glance

Up until April 2020, Verizon, AT&T, T-Mobile and Sprint were the four major cellphone service providers in the United States. There were also a few regional providers, such as U.S. Cellular and C Spire Wireless, and a fringe of local providers, such as Cricket Wireless and TracFone Wireless, which often offered flexible, more economical prepaid plans. Compared to the Big Four, the other providers' network deployment and market presence were almost negligible.[20]

A consumer (or a household) chooses a plan offered by a provider, considering prices, coverage, speed and customer service. A plan typically ranges from $30 to $100. Among the Big Four, Verizon and AT&T were known for the best coverage, while T-Mobile and Sprint were seen as offering comparable deals with lower prices but less coverage. The Federal Communications Commission (FCC) is the main regulator of this industry, while the Department of Justice (DOJ) and the Federal Trade Commission (FTC) share the responsibility for evaluating anti-competitive conduct in this industry.

[20]The Big Four and US Cellular are the only Mobile Network Operators (MNOs) in the continental U.S. — that is, providers that own and control the spectrum licenses and network infrastructure necessary to provide services to subscribers. All other cellphone providers in the U.S. are Mobile Virtual Network Operators (MVNOs), relying on other firms' network infrastructure to provide services.

4.2 Cellular Network Investment

A cellular network is composed of cellphones, base transceiver stations ("cell sites"), mobile telephone switching offices, and the public switching telephone network.[21] When joined together, cellular networks provide radio coverage over a wide geographic area, enabling cellphones to communicate with each other. Globally, major telecommunications providers have deployed cellular networks over most of the inhabited land area on Earth.

Building a cellular network takes decades of physical and financial investment from a provider. In the past few decades, mobile wireless technologies have experienced multiple generations of evolution — namely, from 0G to 5G. In the 2000s, 3G technology was implemented, enabling media streaming with high connection speed. From the start of the 2010s, 4G-LTE was rolled out gradually, accounting for more than half of mobile connections, hitting 52% for the first time in 2019.[22] Cellular networks need to be maintained and updated constantly, with a substantial cost for sustaining network operation. The Global System for Mobile Communications (GSM) Association projected in 2020 that global network operators would invest more than $1.1 trillion in their networks in the next five years.

During our study period, from 2015 to 2018, 4G-LTE grew to be the dominant network technology. The Big Four have constructed their main 4G-LTE networks, but even extending services to an unserved local market from this main network involves millions to billions of dollars. A potential entrant for a local market needs to first acquire spectrum licenses, depending on the size of the market served.[23] A provider then needs to build cell sites, purchase radio transmitters and receivers, and acquire access to intermediate links connecting different wired networks ("backhaul"). The firm also must build a distributional network and market its services to retail consumers. To sum up, the biggest hurdle of deploying a new network technology is the substantial costs involved; these costs can become prohibitive in areas with low population density and rugged terrains. Retiring technologies of previous generations can free up spectrum and existing facilities to accommodate the next generation of

[21] We explain the components and evolution history of cellular networks in Appendix C.

[22] Industry experts predict that 4G will peak at just under 60% by 2023 (The GSM Association Intelligence, "The Mobile Economy 2020.")

[23] A spectrum license gives its holder the exclusive option to use a certain range of frequencies in a well-delineated geographic area. A firm can purchase these licenses in the FCC spectrum auctions or acquire them in secondary markets through purchase or renting. Xiao and Yuan (2021) describe the 2008 FCC auction to sell off 700 MHz, used mainly for 4G-LTE deployment.

technology; at the same time, deploying a new technology in a cluster of nearby markets, simultaneously or sequentially, helps a provider to achieve economies of scale. For these reasons, it is essential to incorporate the "network investment" effect in a potential entrant's evaluation of the expected payoff from entering a local market. When we study providers' decisions to enter local markets, not accounting for the network investment factor means ignoring a first-order difference between Verizon, an industry leader, and Cricket Wireless, a fringe player.

4.3 T-Mobile and Sprint Merger: Policy Considerations

T-Mobile and Sprint announced a merger deal of $26 billion on April 29, 2019. The proposed merger would reduce the number of national providers from four to three, leading to antitrust concerns by state governments and regulating agencies.[24] The merging parties claimed a substantial saving of $43.6 billion via cost synergies, which would allow the merged firm to become a stronger competitor against Verizon and AT&T. Proponents of this merger argued that it would generate broader coverage, greater capacity, higher service quality and a rapid deployment of a nationwide 5G network (Wallsten, 2019). Opponents argued that the reduction in the number of providers would lead to higher prices, fewer choices, lower quality, and a slow roll-out of 5G services.[25]

On July 26, 2019, the DOJ approved the merger after T-Mobile and Sprint reached an agreement to sell Sprint's branded prepaid business,[26] Sprint's entire 800 MHz portfolio, and other assets to the DISH Network ("DISH" henceforth). The DOJ believed that DISH's previous spectrum holdings and the divested assets from the merger would help DISH become the fourth national provider. The DOJ also prescribed detailed operational instructions for DISH to enter as a facilities-based provider instead of just a reseller.[27] The DOJ argued that this remedy would restore the *ex ante* competitive market conditions before the merger. Judge Victor Marrero of the U.S.

[24] Internationally, the telecommunications industry has experienced a wave of consolidation activities recently. Most notably, the European Commission allowed four-to-three mergers in the Netherlands, Austria, Ireland, Germany and Italy, but blocked a similar merger in Denmark (Genakos, Valletti, and Verboven, 2018).

[25] DOJ Complaint, U.S. et al. v. Deutsche Telekom AG, T-Mobile Us, Inc., Softbank Group Corp., and Sprint Corporation, No. 1:19-cv-02232, at 3 (D.D.C. Jul. 26, 2019) Case 1:19-cv-02232, July 26, 2019.

[26] This includes Boost Mobile and Virgin Mobile, representing 9.3 million consumers.

[27] The DOJ imposes on the merging parties an obligation to permit DISH to operate as a reseller on the merged firm's wireless network for the entire seven-year term of the settlement. DISH promised to comply with the network build commitments made to the DOJ by 2023. If DISH's own network does not serve 70% of the country by then, it will face penalties of up to $2.2 billion.

District Court cited the DOJ's remedy as a key factor in approving the merger, noting that it made DISH "well poised to become a fourth [Mobile Network Operator] in the market, and its extensive preparations and regulatory remedies indicate that it can sufficiently replace Sprint's competitive impact". However, opponents questioned the effectiveness of this remedy, calling it "exceedingly optimistic" (Economides et al., 2019) or stating "the Court may have erred in treating DISH as a merger-induced entrant" (Caradonna, Miller, and Shue, 2021).

On October 18, 2019, the merger received formal approval from the FCC in a 3-2 commissioner vote, but attorney generals from 14 states soon filed lawsuits to block the merger. After lengthy negotiations with the states and the DOJ, the merger officially closed on April 1, 2020, with the Sprint brand discontinued on August 2, 2020.

Evaluating the overall effects of the merger on a national level is beyond the scope of this paper. Instead, we focus on evaluating a key claim of the merger's benefit: it would strengthen competition in rural areas and alleviate the inequality in cellular infrastructure across the states (Wallsten, 2019). The pre-merger T-Mobile and Sprint did not have sufficient assets and coverage to compete effectively with the industry leaders, especially in rural areas.[28] The merged firm, aided by "the unique combination of spectrum, sites and equipment of T-Mobile and Sprint",[29] would become a comparable rival to AT&T and Verizon. Opponents of the merger, such as the Rural Broadband Association, argued that T-Mobile had shown little incentive to invest in rural areas, and, therefore, its incentives were unlikely to change following this merger.

We investigate how a hypothetical T-Mobile and Sprint merger in 2016 would have affected the 4G-LTE deployment on local markets that had not been served by most national providers by then. As discussed above, cellphone coverage in unserved and underserved markets is a major policy consideration evaluating the 2020 merger case. No direct empirical evidence, however, is available to support either side of the argument. We also evaluate the remedy proposed by the DOJ, which divests assets from the merger to support DISH as a national provider. We exploit data and a structural model of discrete games with incomplete information to analyze the impact of the hypothetical merger and remedy, taking into account the firms' post-merger network consolidation and strategic responses.

[28]The FCC reported that in December 2016, more than 98% of rural Census blocks had at least one LTE provider, but only 57% had at least four providers, compared to 96% of non-rural blocks.

[29]T-Mobile and Sprint, "Description of Transaction, Public Interest Statement, and Related Demonstrations", June 18, 2018, page 16.

4.4 Data Sources

We use three publicly available data sets to construct our sample. The first is the FCC's Mobile Deployment Form 477 Data from 2015 to 2018, which reports semi-annually each provider's 2G-4G coverage in every U.S. census block.[30] The FCC requires all facilities-based broadband providers to file Form 477, which discloses where they offer Internet access service at speeds exceeding 200 kbps in at least one direction. In particular, for each mobile network technology deployed in each radio frequency band, facilities-based mobile providers must submit polygons representing their nationwide coverage area of that technology and the advertised data upload and download speeds. Providers' submission of data is mandatory, and they must certify the accuracy of the data submitted.

With providers' submitted data on coverage polygons, the FCC reports the percentage of the area in a census block covered by each technology (including 2G, 3G, 4G-non-LTE,[31] and 4G-LTE) by each provider, using a computationally intensive process.[32] In addition, the FCC reports the percentage of a census block covered by "any" technology. From December 2015 to December 2018, the FCC data provide seven snapshots of each firm's granular-level network deployment information. Each snapshot of data has about 45 million observations at the firm-census block level.

The second data set is the 2016 American Community Survey. We obtain aggregate demographic variables such as population size, age, gender and ethnicity profiles, income, and commuting patterns that are potential determinants of a consumer's cellphone use. The third data set is the 2000 Population Census. We use the same variables as the ones we obtain from the 2016 American Community Survey to construct our instrument variables – the lagged demographics of neighboring markets – for endogenous network investment variables. Using information from neighboring markets as instruments is common in industrial organization literature, (e.g. Nevo,

[30]The FCC started to report the Mobile Deployment (including both voice and broadband) data from December 2014, but 2015 was the first year that the FCC reported the actual area coverage within a census block by each provider. Much of the information presented on data description is based on the FCC's Public Notice (DA 16-1107), released on September 30, 2016.

[31]4G-non-LTE refers to technologies that do not reach 4G standards but were marketed as 4G by cellphone providers. 4G-non-LTE will be ultimately replaced by 4G-LTE. Sprint and Clearwire, for example, invested in WiMax rather than LTE and had to rebuild their 4G networks.

[32]The FCC first removes the spectrum and speed information from each shapefile filed by a provider, and then consolidates different polygons for a particular technology for a particular provider into a single, unique polygon. The FCC then determines how much of a census block is covered by this unique polygon. The FCC has not calculated how much the coverage reported for one technology does or does not overlap with coverage of another technology — e.g., 2G and 3G overlap within a census block.

2001). For both data sets, we obtain demographic variables at the census tract level.

4.5 Variable Definition and Sample Construction

With the raw data, we define open markets for 4G-LTE deployment by the four major national providers and then merge in demographic variables at the census tract level.

4.5.1 Aggregation to census tracts

We use the December editions of the FCC's Mobile Deployment Form 477 data from 2015 to 2018, which yield a four-year snapshot of mobile network deployment for the universe of U.S. census blocks. A census block is the smallest geographic unit in the U.S. Census, amounting to more than 11 millions observations in the 2010 Census. A census block is typically a very small geographic area; for example, it is often a city block bounded on all sides by streets, and we do not think that deployment decisions are made on such a fine-grained geographic basis. We therefore aggregate these census blocks to a universe of 73,057 census tracts. A census tract is designed to be a relatively homogeneous unit with respect to population characteristics, economic status and living conditions. In general, each census tract encompasses 2,500 to 8,000 people.[33] A census tract usually covers a contiguous area; however, the spatial size of census tracts varies widely depending on the density of the settlement. A rough estimate of the radius of a typical census tract is 6.5 kilometers.[34] Although cell towers have a maximum range of 50 to 70 kilometers, they are typically spaced two to three kilometers apart to adequately handle cellphone traffic.[35] Based on the above comparison, we define census tracts as geographic markets based on which cellphone providers make investment and network deployment decisions.

For every firm in every census tract, we calculate the percentage of census blocks covered within the census tract by a given technology. The FCC-reported census block coverage has a bipolar distribution, with a small peak between 0% and 10% coverage and a major peak at 100%.[36] We think that some census blocks may experience low, spillover coverage from a nearby cell site in another census block, and this is not an

[33]Due to their size and internal homogeneity, Seim (2006) uses census tracts as location choices for video retail stores.

[34]The total area of the U.S. is 9.857 million square kilometers, covering 73,057 census tracts. A census tract covers 134.9 square kilometers, on average, with roughly 6.5 kilometers as the radius.

[35]In urban areas, cell towers may be 400 to 800 meters apart to accommodate the dense population.

[36]For example, for AT&T and Verizon, the 4G-LTE coverage of a census block was already 100% at the 10th percentile for most of our data period; for T-Mobile and Sprint, this number was at high 90% at the 10th percentile.

actual entry. Therefore, we define a provider's coverage of a census block under a given technology as a dummy variable that equals 0 if the FCC-reported coverage falls below 10%, and 1 otherwise. When we aggregate to census tracts, we use the same reasoning and define the entry dummy for 4G-LTE as 0 if the percentage of census blocks covered by 4G-LTE within a census tract falls below 10%, and 1 otherwise.

4.5.2 Sample construction

For the Big Four, we can safely argue that the national 4G-LTE network was mostly laid out by the end of 2015, and the remaining task was about the leftover, mostly isolated, open markets. We focus on a potential entrant's decisions to enter these local, isolated markets.[37] For each provider, a census tract is defined as an open market for 4G-LTE deployment (an entry decision) if the deployment dummy was 0 in December 2015. We measure each provider's network investment via any generation of technology by the end of 2015. We then use the 2018 data to measure 4G entry into the open markets, treating the time between 2016 and 2018 as a single period in the cross-sectional data. We decide to focus on the leftover, often isolated, open markets at the end of 4G-LTE deployment and to lump a three-year period into a cross section in order to alleviate the concerns that firms make forward-looking decisions in a dynamic oligopoly game. We think our choice of a static entry game framework captures the first-order strategic considerations in this setting.

To summarize, from 2016 to 2018 the Big Four were the main competitors in the U.S cellphone industry, and they were strategically considering whether to enter the few remaining, scattered, markets left open to 4G-LTE deployment. We define a potential entrant to a market as a Big Four provider who had no 4G-LTE deployment in the market by the end of 2015, but had operated in at least one census tract in that state. A potential entrant is observed as having decided to enter a market if it made 4G-LTE deployment by the end of 2018.[38] Our sample consists of 2,582 Census tracts that have at least two potential entrants by the end of 2015.

4.5.3 Summary statistics: the Big Four's cellphone deployment

In Table 1, we present summary statistics of the Big Four's cellphone technology deployment in their open 4G-LTE markets by the end of 2015. Of the 2,582 census

[37] A firm usually needs to obtain approval from a state before entry (Fan and Xiao, 2015). If a firm had not operated in a single census tract in a state, we do not consider this firm as a potential entrant to any census tracts of the state. Verizon and AT&T had operated in all states (including the District of Columbia); T-Mobile had entered 50 states and Sprint 49 states.

[38] We keep the other fringe competitors when counting the number of incumbents in a census tract.

tracts in our sample, Verizon had not entered 645 by the end of 2015 (i.e., no 4G-LTE deployment by the end of 2015); AT&T, 1,132 markets; T-Mobile, 2,185 markets; and Sprint, 2,182 markets. Table 1 shows how the Big Four differed in their technology mix of 2G, 3G, 4G-non-LTE, and 4G-LTE. From 2016 to 2018, Verizon focused almost completely on 4G-LTE; AT&T retired 2G and pushed for 3G, 4G-non-LTE, and 4G-LTE, with 4G-LTE leading the growth; T-Mobile grew all four technologies, again with 4G-LTE making the largest strides; Sprint never deployed 4G-non-LTE and made relatively small steps compared to its rivals. Of the four technologies, 4G-LTE is the one that experienced the most growth across the board from 2015 to 2018. The 4G-LTE growth is also reflected by the percentage of 4G-LTE coverage in other tracts of the same county (referred to as "neighboring tracts" henceforth) and the number of incumbents offering 4G-LTE in the focal markets.

We use two network investment variables to capture the existing facilities owned by a potential entrant (firm k) in the focal market and nearby areas. The first is the firm's 3G deployment in the focal market by the end of 2015 (denoted by $X_{k2,1}$). The second is the firm's 4G-LTE deployment in neighboring tracts by the end of 2018 (denoted by $X_{k2,2}$). As we discussed in Section 5.2, different generations of cellphone technologies can share basic facilities (e.g., cell towers), and nearby cell sites reduce the cost of extending the network extra miles (e.g., nearby conduits can be extended to bordering neighborhoods). Therefore, $X_{k2,1}$ and $X_{k2,2}$ are shifters for a provider k's entry decision into the focal market.

A potential entrant's network investment can be measured in different dimensions. For robustness, we use a potential entrant k's deployment via *any* previous generation before 4G-LTE in the focal market by the end of 2015 as $X_{k2,1}$, and its 4G-LTE deployment in neighboring tracts by the end of 2015 as $X_{k2,2}$. We discuss the robustness of our results under different measurements of $X_{k2,1}$ and $X_{k2,2}$ in Appendix D. These robustness checks only lead to marginally different point estimates, and conform to the main conclusion in our estimation and counterfactual analyses.

4.5.4 Summary statistics: market attributes

In Table 2, we compare the market attributes of the census tracts in the sample (2,582 in total) for our entry game and those of the remaining parts of the country (70,745 in total). The most important determinant of entry is population size. Demand for cellphone services depends on market demographics such as gender, age, ethnicity profiles,

Table 1: Cellphone Service Coverage (2015-2018), by the Big Four

	2015		2018	
Variable	Mean	S.D.	Mean	S.D.
Verizon: potential entrant to 645 tracts				
% blocks with 2G	0.007	0.052	0.019	0.106
% blocks with 3G	0.005	0.043	0.016	0.094
% blocks with 4G-non-LTE	0	0	0	0
% blocks with 4G-LTE	-	-	0.122	0.233
% blocks 4G-LTE, neighbor tracts average	0.447	0.301	0.534	0.365
# incumbents with 4G-LTE	1.297	1.108	1.964	1.460
Entry with 4G-LTE	-	-	0.267	0.443
AT&T: potential entrant to 1,132 tracts				
% blocks with 2G	0.233	0.357	0	0
% blocks with 3G	0.384	0.414	0.468	0.433
% blocks with 4G-non-LTE	0.357	0.409	0.403	0.424
% blocks with 4G-LTE	-	-	0.362	0.396
% blocks 4G-LTE, neighbor tracts average	0.336	0.372	0.545	0.334
# incumbents with 4G-LTE	1.479	0.877	2.511	1.329
Entry with 4G-LTE	-	-	0.542	0.498
T-Mobile: potential entrant to 2,185 tracts				
% blocks with 2G	0.046	0.163	0.133	0.312
% blocks with 3G	0.011	0.083	0.164	0.315
% blocks with 4G-non-LTE	0.003	0.032	0.243	0.366
% blocks with 4G-LTE	-	-	0.496	0.423
% blocks 4G-LTE, neighbor tracts average	0.206	0.326	0.534	0.326
# incumbents with 4G-LTE	1.876	0.821	3.011	1.195
Entry with 4G-LTE	-	-	0.648	0.478
Sprint: potential entrant to 2,182 tracts				
% blocks with 2G	0.154	0.314	0.195	0.345
% blocks with 3G	0.147	0.309	0.173	0.326
% blocks with 4G-non-LTE	0	0	0	0
% blocks with 4G-LTE	-	-	0.208	0.358
% blocks 4G-LTE, neighbor tracts average	0.107	0.231	0.259	0.317
# incumbents with 4G-LTE	2.055	0.787	3.286	1.015
Entry with 4G-LTE	-	-	0.293	0.455

Notes: This table is based on 6,244 tract-firm observations (2,582 Census Tracts, two to four potential entrants in each tract). This table reports the Big Four's coverage of census blocks by each generation of technology, summarized over Census tracts each firm has yet to enter with 4G-LTE by the end of 2015.

Table 2: Census Tract Attributes

Variable	Definition	Markets to enter Mean	Markets to enter S.D.	Other markets Mean	Other markets S.D.
Pop (in 1,000's)	Population in thousands	2.901	1.758	4.414	2.171
% Female	% female in population	0.495	0.045	0.508	0.050
% Senior	% 65 and older in population	0.285	0.266	0.153	0.092
% White	% White in population	0.862	0.209	0.724	0.253
% Black	% Black in population	0.038	0.107	0.142	0.222
% Native	% Native in population	0.044	0.161	0.008	0.035
% Asian	% Asian in population	0.012	0.037	0.049	0.091
% Hispanic	% Hispanic in population	0.072	0.129	0.163	0.215
% College	% above 25, with college degree	0.193	0.092	0.294	0.190
% Labor force	% above 16, in labor force	0.573	0.109	0.631	0.103
% Work home	% above 16, employed, working at home	0.056	0.047	0.045	0.040
% Long comm.	% above 16, employed, commuting for 40+ minutes	0.167	0.106	0.201	0.129
HH income	Median household income in Year 2016 ($1,000's)	46.127	14.499	59.641	29.860
HH size	Household size	4.651	5.688	2.915	1.835
Pop density	Population/land area	0.0002	0.0007	0.002	0.005
% Rural	% population in rural area	0.683	0.404	0.190	0.348
Mostly water	If water area ≥ 90%	0.113	0.317	0.0007	0.027

Notes: This table is based on 73,057 Census tracts, which include 2,582 tracts for the final sample we use for estimation and 70,475 tracts for the rest of the data.

education, labor force participation, household income and size. Workers' commuting patterns also contribute to the intensity of cellphone use. Lastly, population density, ruralness and the presence of large areas of water can be considered cost shifters for network deployment.

As shown in Table 2, the 2,582 census tracts, which have at least two Big Four potential entrants, are notably different from the rest of the country in all dimensions. They have much smaller populations and very different demographic compositions. They are more rural, more sparsely-populated, poorer and less educated. They spend more time working from home and less time commuting to work. In short, these markets seem to belong to the bottom side of the "digital divide," which refers to the significant disparity in Internet access across different demographic groups and geographic areas in the country.

4.6 Instrumental Variables

To specify our Equations (1) to (4) in this cellphone 4G-LTE entry game application, we reiterate our notation:

- Y_k: potential entrant k's 4G-LTE entry decision;
- X_{k1}: tract attributes from 2016 ACS + the number of 4G-LTE incumbents in the focal census tract by the end of 2015;[39]
- X_{k2}: includes two components – potential entrant k's 3G deployment in the focal census tract, $X_{k2,1}$, and its 4G-LTE deployment in neighboring tracts, $X_{k2,2}$;
- Z_k: instrumental variables for $X_{k2,1}$ and $X_{k2,2}$ (the past attributes of neighboring tracts in 2000);
- u_k: unobserved errors in the *ex post* payoffs (Equation (1));
- V_k: unobserved errors in $X_{k2,1}, X_{k2,2}$ (Equation (2)).
- η_k: residual private shocks after we control for V_k (Equation (5))

In the specification above, we focus on 4G-LTE competition. That is, we do not consider a provider that had offered only 3G service as of 2015 as a competitor in the 4G-LTE deployment game. We have two endogenous covariates in a potential entrant's expected payoff function: $X_{k2,1}$ and $X_{k2,2}$. In this subsection, we discuss our choice of instruments Z_k for these endogenous variables.

In a firm's decision rule (Equation (5)), the unobserved error η_k is a potential entrant's private information. The potential entrant observes its own η_k, but not the others', before deploying different generations of technology in the focal and nearby markets. A good example of this unobserved term is each firm's cost of deployment, maintenance and operating in the focal market. In contrast, V_k, can be backed out from the auxiliary equation that explains the source of endogeneity. A good example of V_k is a firm's spectrum holdings and lease/roaming agreement in the focal market. Valid instruments for X_{k2} need to be relevant for the "network investment" variables, to be excluded from the entry payoff function, and to be orthogonal to η_k and V_k. For each focal census tract, we use demographics of its "neighbors" (i.e., other tracts in the

[39]We treat the number of incumbents as predetermined and uncorrelated with the unobserved u_k in the entry payoff equation. An incumbent's entry decision was made earlier, before the realization of a potential entrant's time-varying private shocks.

same county) in 2000 as instruments for $X_{k2,1}$ and $X_{k2,2}$. Below we discuss why these instruments satisfy the three properties required.

First, relevance. These lagged demographic variables of neighbors affect 4G-LTE deployment in the neighboring markets directly, and, therefore, are relevant for $X_{k2,2}$. They are relevant for $X_{k2,1}$ (the focal market's 3G deployment) through a "spillover effect". That is, the instruments affect the 3G deployment in the neighboring markets, which, in turn, could lower the cost of 3G deployment in the focal market. Through the direct effects on the neighboring markets and the spillover effect to the focal market, these instruments are relevant to the two endogenous, "network investment" variables in our main equation.

Second, exclusion. These lagged demographic variables of neighboring tracts are excluded from the main equation because they do not directly enter the structural form of 4G-LTE deployment payoffs on the focal market, which already conditions on the focal market's observable demographics, its 3G deployment and its neighbors' 4G-LTE deployment. One may worry that a potential entrant makes entry decisions on a much larger scale than a census tract, so these instruments may enter the payoff function of the focal market. However, as explained earlier, our sample consists of tracts that had not been entered by most major providers as of 2016. These tracts were typically isolated, with the surrounding tracts already served by 4G-LTE before the start of our sampling period. This is shown in Table 1's summary statistics on the percentage of census blocks covered with 4G-LTE in the neighboring tracts. Therefore, we believe modeling the Big Four providers' post-2015 4G-LTE deployment decisions at the level of local markets serves as a first-order approximation that captures the firms' main strategic concerns.

Lastly, orthogonality. It is plausible to assume that these lagged demographics on neighboring tracts are orthogonal to the unobserved factors determining deployments in focal and neighboring markets (η_k and V_k), once conditional on market-level observables. We choose neighboring markets' attributes in 2000 (instead of in 2016) as our instruments to lend more credibility to the above claim. First, 3G technology was actively deployed between 2000 and 2010; therefore, the 2000 Census's market attributes are more relevant to 3G deployment. Second, the correlation between 2000 Census's market attributes and 2016's market-level unobserved heterogeneity is weakened over time, giving us better justification for the orthogonality of the instruments. For example, a firm's spectrum holdings in 2016 (likely sources of V_k) are less correlated with neighboring markets' attributes in 2000, after multiple generations of cellphone technology evolution and secondary market trading. Lastly, we believe that the detailed market-level attributes included in X_{k1} have already captured the spatial correlation across census tracts. Thus we abstract away from spatial correlation in the unobservables. That is, conditional on X_{k1}, the unobservables η_k and V_k, which capture firm- and market-specific heterogeneity, are not spatially correlated. To check instrument strength and relevance, we test the joint significance of these instruments in Equation (2). For the equation that explains $X_{k2,1}$, the F-statistic is 8.514 with a p-value less than 0.001; for $X_{k2,2}$, the F-statistic is 46.19 with p-value less than 0.001.

4.7 Estimation Results

Among the Big Four, AT&T and Verizon lead in terms of spectrum holdings, network built and customer base. Our baseline specification categorizes AT&T and Verizon as "strong" potential entrants and T-Mobile and Sprint as "weak" ones. Analogous to our Monte Carlo exercise, we estimate heterogeneous competitive effects based on whether the potential entrant is strong or weak in terms of deployment, relative to competitors. We hypothesize that "weak" potential entrants will suffer larger competition effects because they are less able to secure market shares facing competition. We present results treating all four firms as equal competitors in Appendix D. We adopt a specification in which the coefficients are not firm-specific (except for the aforementioned heterogeneous competition effects) in *ex post* payoffs. Thus, for simplicity, we suppress the index k in $X_{k2,1}, X_{k2,2}, V_{k1}, V_{k2}$ when reporting our estimation and simulation results.

Table 3 presents estimation results from two models, with and without accounting for endogeneity in X_2 respectively. In the former model, we include all exogenous and instrumental variables and their squared terms (excluding dummy variables) in the first stage estimation (the first-stage results are reported in Appendix E). In the latter model, all covariates in X_1 and X_2 are considered exogenous in MLE estimation. Using our estimator in Section 3 to allow for endogenous X_2, we get estimates that mostly conform to our expectations. The "expected competition" effects (α_k) are significantly negative, with a larger effect on weak potential entrants as we hypothesized. The incumbent effect is also significantly negative. Population size contributes to 4G-LTE entry positively, but the percentages of seniors, Natives and Hispanics, as well as water coverage, act in the opposite direction. The percentage of labor force participation contributes to 4G-LTE entry negatively, which can be rationalized as labor force participation has no clean-cut relationship with the willingness to pay for mobile phone services. For example, if a Census tract has a lot of low-end jobs that do not pay well, then higher labor force participation will not necessarily translate into greater willingness to subscribe to 4G-LTE. The percentage of rural population, likewise, has an ambiguous relationship with such willingness to pay. For example, residents who live in a rural area may be willing to spend on better mobile coverage to stay connected.

Allowing for potential endogenous X_2's turns out to have a big impact on the estimates of network investment effects. Both models produce significantly positive estimates for the coefficients of X_2's, but ignoring the endogeneity in X_2 underestimates the effect of $X_{2,1}$ while over-estimating that of $X_{2,2}$. The reason for such discrepancies can be attributed to the roles of structural errors (Vs) in the expected entry payoff. These Vs are firm- or market-level heterogeneity. Different Vs may contribute to 3G/4G-LTE deployment in the focal market and 4G-LTE deployment in the neighboring markets in different directions.

As noted earlier, a good example of V's that can lead to these patterns is each firm's spectrum holdings for different generations of cellphone technology. A firm knows its own spectrum holdings and usually has a rough idea of its rivals' spectrum holdings, because the FCC's spectrum auctions are public information and trading/leasing/roaming agreements are often industry knowledge. The spectrum of a certain frequency often best serves a particular generation of cellphone technology and has different suitability for urban, suburban and rural deployment. For example, 700 MHz is considered the right band for 4G-LTE, while 2.5GHz is right for 5G. A firm may have a rich stock of 3G spectrum but a poor stock of 4G-LTE spectrum, simply due to budget constraints.[40] The negative correlation between a firm's 3G and 4G-LTE spectrum holdings in a focal market (which are captured in V_1 and u, respectively) is consistent with a negative coefficient for V_1 in our estimates, which account for endogenous $X_{2,1}$. In addition, this negative correlation also explains the negative bias in the estimated coefficient for X_{21} when its endogeneity is ignored (i.e., 2.024<3.757).

At the same time, note that if a firm owns a 4G-LTE spectrum license for the focal census tract, this license covers at least the entire county due to its indivisible nature.[41] Hence, there is positive correlation between the 4G-LTE spectrum holdings in the focal

[40] For example, T-Mobile did not (and still does not) have enough low-band spectrum (600 MHz), which has wider reach and is better suited for rural deployment; instead, it relies on 1,700MHz and 1900MHz for 4G-LTE deployment, which is better suited for urban and suburban areas.

[41] The FCC's smallest coverage for a spectrum license is the Cellular Market Area, which typically covers three to four counties. Even if firms divide spectrum licenses for resale and lease in secondary markets, they do not break down counties (Kavalar, 2014).

and neighboring markets (captured by u and V_2, respectively). This is consistent with a positive coefficient for V_2 in our estimates accounting for endogenous X_2, and it leads to a positive bias in the estimated coefficient for $X_{2,2}$ when endogeneity is ignored (i.e., 3.042>1.618).

4.8 Counterfactual Results: Evaluating the Merger and the Merger Remedy

In this section, we investigate the impact of a hypothetical merger between T-Mobile and Sprint in 2016. In the first scenario, we use the structural estimates from Table 3 to simulate market outcomes under a baseline scenario with no mergers. In the second scenario for simulation, T-Mobile and Sprint are merged into a "strong" competitor with integrated T-Mobile and Sprint network (henceforth referred to as a “New T-Mobile”).[42] In the third scenario, we introduce DISH as a new potential entrant. It is modeled as a “weak competitor” that takes over the decommissioned network originally owned by Sprint. That is, in this scenario, the T-Mobile and Sprint merger is mandated to divest assets to the new competitor DISH, enabling DISH’s entry as a facilities-based provider. This scenario corresponds to the DOJ’s proposed remedy based on anti-trust concerns. We keep all 2,582 open markets in the baseline simulation, which has a combined total population of 17,209,450.[43]

We use the estimated coefficients in Table 3 to simulate the local market entry decisions of Verizon, AT&T and New T-Mobile (and DISH in the third scenario). For comparison, in each scenario, we simulate two sets of outcomes, one with and one without accounting for endogenous X_2. Panel A in Table 4 presents the simulated market entries across different scenarios; Panel B in Table 4 reports the population still underserved (that is, the population with the number of providers less than or equal to one) by the end of 2018 across these scenarios.

[42] After the merger, T-Mobile will bridge the two network cores by routing Sprint traffic to the T-Mobile anchor network. An estimated 11,000 Sprint cell sites will be retained to improve capacity and/or coverage in the new network. We implement the after-merger network integration in data by taking the union or the maximum of T-Mobile’s and Sprint’s coverage at the census block level. These two methods yield almost identical results because, in census tracts where both firms serve, they serve mostly at 100% coverage. We report the maximum result in the paper.

[43] If either T-Mobile or Sprint was a 4G-LTE incumbent in a census tract in 2015 and the other was a potential entrant, we assume that after the merger, New T-Mobile will re-evaluate the profitability of the market and decide about entry again. In this case, and in the case that Sprint was a 4G-LTE incumbent in a census tract in 2015, the number of incumbents in 2016 will be reduced by one after the merger.

Table 3: Estimation Results of the 4G-LTE Entry Game: Structural Coefficients

	Treating X_2 as Endogenous		Treating X_2 as Exogenous	
	(1)		(2)	
Variable	Estimate	Std. Error	Estimate	Std. Error
Pop (in 1,000's)	0.078***	0.020	0.081***	0.019
% Female	0.437	0.761	0.417	0.758
% Senior	-1.035**	0.414	-1.110***	0.425
% White	-0.233	0.513	-0.170	0.515
% Black	-0.351	0.526	-0.367	0.535
% Native	-1.396***	0.536	-1.611***	0.518
% Asian	0.870	1.310	1.290	1.316
% Hispanic	-0.469	0.339	-0.185	0.308
% College	-0.150	0.403	-0.063	0.417
% Labor force	-0.943***	0.322	-0.627**	0.314
% Work home	0.289	0.522	0.768	0.588
% Long comm.	0.069	0.307	-0.508*	0.297
HH income	-0.002	0.003	-0.006**	0.003
HH size	-0.042	0.026	-0.059**	0.026
Pop density	-0.131	0.089	-0.229***	0.084
% Rural	0.223*	0.126	0.188**	0.092
Mostly water	-1.850***	0.550	-2.418***	0.545
# Incumbents	-0.158***	0.043	-0.225***	0.042
Intercept	0.911	0.784	0.871	0.757
Network Investment Effects				
$X_{2,1}$	3.757***	0.790	2.024***	0.178
$X_{2,2}$	1.618***	0.323	3.042***	0.096
V_1	-1.738**	0.784	–	–
V_2	1.536***	0.335	–	–
Expected Competition Effects				
Strong potential entrant	-1.070***	0.090	-1.084***	0.085
Weak potential entrant	-1.105***	0.061	-1.133***	0.064

Notes: The results are based on 6,244 potential entrants for 2,582 Census tracts (each with at least two potential big-4 entrants). Standard errors are obtained by resampling the markets with replacement for 1,000 times. Asterisks indicate the statistical significance at the 1% (***), 5% (**), and 10% (*) levels. The estimated competitive effects satisfy the moderate interaction condition in Assumption 2 on 95.7% of markets in the sample.

Columns (1) to (3) of Table 4 are simulation results under the three scenarios, using structural estimates that account for endogeneity (column (1) of Table 3). Comparing column (1) to column (2), we can see that the T-Mobile and Sprint merger reduces the number of total entry occurrences from 2,898 to 2,264, which is a 21.88% reduction. This leads to a large increase (23.15%) in the underserved population. There are two explanations for such a reduction: First, there are fewer potential entrants on the markets after the merger. Second, the New T-Mobile resulting from the merger is a strong competitor with integrated network from Sprint and T-Mobile and, therefore, the entry probability of the merged firm is higher than that of T-Mobile or Sprint alone. That also impacts how the merger deters entry by the other competitors. These two effects can also explain the simulated increase in the number of markets with no Big-4 entrant under the T-Mobile/Sprint merger in column (2). On the one hand, the post-merger New T-Mobile may well benefit from an economy of scale due to the combined network investment, and consequently has stronger profit incentives for entry; on the other hand, our simulation indicates that such an increase in the entry likelihood of the single, merged entity is not substantive enough to off-set the negative impact on entry occurrence due to fewer potential entrants and the equilibrium responses by the other Big-4 competitors (AT&T and Verizon). As for each firm's entry occurrences after the merger, New T-Mobile would gain sizable ground after the merger (compared to the pre-merger T-Mobile), while AT&T and Verizon would stay roughly the same. Overall, the reduction of total instances of market entry after the merger is due mainly to the fact there would be fewer potential entrants.

Now, consider the scenario in which DISH is introduced after the merger as a fourth competitor, enabled by the mandated divestiture from the New T-Mobile. We assume the most optimistic scenario, which is that DISH is able to achieve Sprint's deployment in 2015 after entry. Column (3) of Table 4 reports that the number of entry occurrences is 2,940, substantially higher than in the scenario without the divestiture required by the DOJ. This practically restores the level of market entries in the baseline scenario without the merger. On most dimensions of entry outcomes and population covered, the DISH remedy seems to be effective. Despite the entry occurrences under the DISH remedy, in fact, is even higher than the baseline (2,940 vs. 2,898), the total population underserved would increase by 3.24% from column (1) to column (3). We checked entry patterns of each firm, and discovered that firms would choose to enter different census tracts after the (remedied) merger, leading to a change in the composition of markets served. In this simulation, we have DISH assuming exactly the same network deployment as Sprint in 2015, and AT&T and Verizon staying the same as before.

Table 4: Counterfactual Results under Alternative Models

	Treating X_2 as Endogenous			Treating X_2 as Exogenous		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Entry outcomes						
# markets with	Baseline	4 to 3	DISH	Baseline	4 to 3	DISH
n entrants = 0	522	633	516	524	578	521
n entrants = 1	1,277	1,641	1,244	1,277	1,677	1,234
n entrants = 2	730	300	771	730	319	770
n entrants = 3	50	8	51	49	8	53
n entrants = 4	2	–	–	3	0	5
Total # entry occurrences	2,898	2,264	2,940	2,893	2,338	2,951
by AT&T	716	727	714	716	740	717
by Verizon	157	171	150	155	186	152
by T-Mobile/New T-Mobile	1,201	1,366	1,262	1,194	1,412	1,258
by Sprint/DISH Network	824	–	814	827	–	824
Panel B: Population (in 1,000's) under-served (# incumbents in 2018 $\leq$ 1)						
Underserved population	Baseline	4 to 3	DISH	Baseline	4 to 3	DISH
Total population	216	266	223	226	263	224
Minority population	122	135	124	124	132	123
Rural population	162	196	165	167	196	166

Notes: For each market, we make 1,000 random draws of the error vector, and use the structural estimates from Table 3 to generate 1,000 counterfactual predictions. The table reports average predictions (rounded to the nearest integer). The above results are based on 2,582 census tracts, each with at least one potential entrant from the Big Four. In Panel A, the number of entrants does not include the number of incumbents prior to 2016; in Panel B, the number of incumbents in 2018 includes both the incumbents prior to 2016 and the entrants between 2016 and 2018.

T-Mobile is the only firm with big changes: New T-Mobile not only has a stronger network, but also becomes a "strong" potential entrant after the merger. The change in the composition of market entered is a strategic, equilibrium response due to the different configuration of network investment and competitors of different status in the markets.

Columns (4) to (6) of Table 4 report simulation results using estimates that do not account for endogeneity in 3G and neighboring 4G-LTE deployment (the first column in panel (2) of Table 3). A comparison between column (1) and column (4) suggests the impact of ignoring endogeneity in X_2 on simulated entries under the baseline scenario is negligible. The predicted changes in market entry under the second (4-to-3 merger) and third (merger + DOJ-mandated divestiture) scenarios in columns (5) and

Table 5: Merger Evaluation under Alternative Models

	4 to 3 merger effects = (4 to 3 - baseline)/baseline		DISH remedy effects = (DISH - baseline)/baseline	
	(1)	(2)	(3)	(4)
	Endogenous X_2	Exogenous X_2	Endogenous X_2	Exogenous X_2
Total # entry occurrences	-21.88%	-19.18%	1.45%	2.00%
# markets with 0 entrant	21.26%	10.31%	-1.15%	-0.57%
# markets with 1 entrant	28.50%	31.32%	-2.58%	-3.37%
Population (in 1,000's) under-served (# incumbents in 2018 ≤ 1)				
Total population	23.15%	16.37%	3.24%	-0.88%
Minority population	10.66%	6.45%	1.64%	-0.81%
Rural population	20.99%	17.37%	1.85%	-0.60%

Notes: The above results are calculated using Table 4 results.

(6), however, are very different from those predicted in columns (2) and (3). We create Table 5 to compare the magnitudes of merger effects and remedy effects under these two models.

As Table 5 shows, if we ignore endogeneity in X_2, we will significantly underestimate the effect of the T-Mobile and Sprint merger on the reduction of entry and on the population affected by reduced entry. Specifically, the number of unserved markets will increase by 21.26% with the 4-to-3 merger under the endogenous X_2 model but only 10.31% if the endogeneity in X_2 is ignored in estimation and simulation. Underestimation of similar magnitude also happens for population affected by reduced entry. For example, the merger will lead to 23.15% increase in population underserved and 20.99% increase in rural population underserved under the endogenous X_2 model but only 16.37% and 17.37% in corresponding metrics under the exogenous X_2 model. The DISH remedy (merger + DOJ-mandated divestiture to DISH) effects predicted by the exogenous X_2 model are more optimistic than those predicted under the model with endogenous X_2. The model with exogenous X_2 slightly over-estimates the percentage increase in entry occurrence under the DISH remedy. It also suggests the DISH remedy would even lead to small reductions in the under-served population, while the model that accounts for endogenous X_2 indicates the remedy will actually lead to non-trivial increases in the under-served population. The key message is that researchers would paint a much rosier picture of the consequences due to the merger and the impact of the DISH remedy if they were to use a model that does not account for X_2's endogeneity. Relying on such a biased prediction, policy makers would lean more toward approving the proposed merger.

5 Conclusion

The literature on discrete choice games is silent on how to deal with endogenous covariates, which is often the focus of empirical exercises. An example of potentially endogenous covariates in firm profits from market entry is the continuous measure of airport presence in Berry (1992). Another example is a grocery store's distance to a supercenter in Grieco (2014), as supercenter locations are endogenous outcomes of a related game at a grander level and possibly correlate with the unobserved heterogeneity of rural markets to be entered by smaller stores. In these studies, the potentially endogenous variables are treated as exogenous. The empirical literature so far has not provided researchers with means to accommodate both the effect of competition (or social interaction) and that of the endogenous covariates in a discrete game setting.

We fill in this gap, proposing a new method for estimating discrete games with incomplete information in the presence of endogenous covariates. The approach is flexible enough to accommodate endogeneity due to player- or game-level unobserved heterogeneity. We apply the method to estimate an entry game of 4G LTE deployments between major wireless service providers in the U.S. In this setting, existing 3G network investment and neighboring 4G-LTE investment are endogenous covariates. We find that a hypothetical merger between T-Mobile and Sprint would reduce 4G-LTE deployment significantly in our sample and that the divestiture remedy would not completely reverse the negative outcomes of the merger. More importantly, we show that incorporating the endogeneity of network investment affects our estimates of economic primitives, the counterfactual simulations under the hypothetical merger, and the policy implications. Both the merger and the remedy would lead to changes in the composition of markets entered and, in turn, different populations covered by cellphone services, and the effects captured by a model with endogenous network investment differs from those ignoring such endogeneity. Based on our results, we recommend that competition and regulatory authorities fully consider the multi-dimensional trade-offs between market power effects and efficiency gains from drastic changes in market structure due to mergers or entry and exit events.[44]

[44]This point is illustrated well by Bourreau, Sun, and Verboven (2021), which shows that new entry in the French mobile telecommunications market led to a flurry of "fight brands" by incumbents.

Individual and firms weigh their decisions upon all available information in strategy settings, but not all of it is captured by observed covariates in empirical models. Some observed covariates are correlated with the player- and game-level unobserved heterogeneity. There are many analogies in applied microeconomics, in which it is essential that researchers incorporate endogenous variables to study a key decision. In labor economics, a worker's career choice depends on her accumulation of human capital. In industrial organization, a pharmaceutical company's patenting decision depends on its stock and flow of innovative activities; a cable TV network's decision to discontinue a TV series depends on the series' rating and viewership. We hope our method will provide a useful tool to identify multiple parameters of interest and, in turn, improve researchers' ability to diagnose, predict and recommend policy remedies.

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Appendix A Proofs

Proof of Lemma 1. The existence of BNEs follows from the continuity of the mapping Γ and an application of the Schauder Fixed-point Theorem. We show the uniqueness of BNE by contradiction.

Suppose that there are two distinct BNEs, $P^1 \equiv (P_1^1, \cdots, P_K^1) \neq (P_1^2, \cdots, P_K^2) \equiv P^2$. From Equation (6), we have

$$|P_k^1 - P_k^2| = \left| f_k\Big(X'_{k1}\beta_k + X'_{k2}\gamma_k + \alpha_k \sum_{j\neq k} \tilde{P}_j + \sum_{j\in\mathcal{K}} V'_j \lambda_{k,j}\Big) \cdot \alpha_k \cdot \sum_{j\neq k} (P_j^1 - P_j^2) \right|$$
$$\leq \sup_t f_k(t) \cdot |\alpha_k| \cdot (K-1) \max_{j\in\mathcal{K}} |P_j^1 - P_j^2| < \max_{j\in\mathcal{K}} |P_j^1 - P_j^2|,$$

where $\tilde{P} = (\tilde{P}_1, \cdots, \tilde{P}_K)$ is a vector of probabilities between P^1 and P^2. The first equality is due to the Mean Value theorem, and the second inequality is due to Assumption 2. Taking maximization of the left-hand side over $\mathcal{K}$ leads to a contradiction: $\max_{k\in\mathcal{K}} |P_k^1 - P_k^2| < \max_{j\in\mathcal{K}} |P_j^1 - P_j^2|$. □

Proof of Theorem 1. (Consistency of $\widehat{\theta}_{2SNPL}$) First, we show that $L_n(\cdot, \cdot; \widehat{\Pi}) \xrightarrow{p} L_0(\cdot, \cdot)$ uniformly over $\Theta \times P$. By the mean value theorem, for any $\theta \in \Theta$, $P \in \mathcal{P}$,

$$L_n(\theta, P; \widehat{\Pi}) - L_n(\theta, P; \Pi_0) = \nabla_\Pi L_n(\theta, P; \Pi^+)(\widehat{\Pi} - \Pi_0), \tag{11}$$

where Π^+ denotes an intermediate value between $\widehat{\Pi}$ and Π_0. By (11) and the triangular inequality,

$$\sup_{\theta,P} \left| L_n(\theta, P; \widehat{\Pi}) - L_0(\theta, P) \right|$$
$$\leq \sup_{\theta,P} |\nabla_\Pi L_n(\theta, P; \Pi^+)| \left| \widehat{\Pi} - \Pi_0 \right| + \sup_{\theta,P} |L_n(\theta, P; \Pi_0) - L_0(\theta, P)|.$$

Under our maintained conditions, $\sup_{\theta,P} |\nabla_\Pi L_n(\theta, P; \Pi^+)| = O_p(1)$. Because $\widehat{\Pi} \xrightarrow{p} \Pi_0$, the first term on the right-hand side of the inequality is $o_p(1)$. By Assumption 4-(ii) and the fact that $l_i(\theta, P; \Pi_0)$ is continuous at each θ, P with probability one, the second term on the right-hand side of the inequality is $o_p(1)$. This establishes the uniform convergence of L_n to $L_0(\cdot)$ over $\Theta \times \mathcal{P}$.

Note that, by Assumption 3-(ii) and the Kullback-Leibler information inequality,

(θ_0, P^0) uniquely maximizes $L_0(\theta, P)$ in the set Λ_0. Define

$$T(\theta, P; \Pi_0) \equiv \max_{c\in\Theta} \Big\{L_0(c, P; \Pi_0)\Big\} - L_0(\theta, P; \Pi_0),$$

where we write out dependence of L_0 on Π_0 explicitly. Because $L_0(\theta, P; \Pi_0)$ is continuous and $\Theta \times \mathcal{P}$ is compact, Berge's maximum theorem establishes that $T(\theta, P; \Pi_0)$ is a continuous function. By construction, $T(\theta, P; \Pi_0) \geq 0$ for any (θ, P). Define

$$\mathcal{E} \equiv \Big\{(\theta, P) \in \Theta \times \mathcal{P} : P = \Gamma(\theta, P; \Pi_0)\Big\}.$$

Since $\Theta \times \mathcal{P}$ is compact and Γ is continuous, $\mathcal{E}$ is a compact set. By definition, Λ_0 is a subset of $\mathcal{E}$. For each element in Λ_0, consider an arbitrarily small open ball that contains it. Let $B_\epsilon(\theta_0, P^0)$ denote the union of such open balls containing elements of Λ_0. Let B_ϵ^c denote the complement of B_ϵ. We then see that $B_\epsilon^c(\theta_0, P^0) \cap \mathcal{E}$ is also compact. Define the constant

$$\tau \equiv \min_{(\theta,P)\in B_\epsilon^c(\theta_0,P^0)\cap\mathcal{E}} T(\theta, P; \Pi_0) > 0. \tag{12}$$

Define the event

$$A_n \equiv \Big\{\Big|L_n(\theta, P; \widehat{\Pi}) - L_0(\theta, P; \Pi_0)\Big| < \tau/2 \text{ for all } (\theta, P) \in \Theta \times \mathcal{P}\Big\}.$$

Let $\Big(\theta_n^*, P_n^*\Big)$ be an element of Λ_n. Then, A_n implies that

$$L_0\Big(\theta_n^*, P_n^*; \Pi_0\Big) > L_n\Big(\theta_n^*, P_n^*; \widehat{\Pi}\Big) - \frac{\tau}{2}; \text{ and}$$
$$L_n\Big(\theta, P_n^*; \widehat{\Pi}\Big) > L_0\Big(\theta, P_n^*; \Pi_0\Big) - \frac{\tau}{2} \text{ for any } \theta \in \Theta.$$

Besides, $L_n\Big(\theta_n^*, P_n^*; \widehat{\Pi}\Big) \geq L_n\Big(\theta, P_n^*; \widehat{\Pi}\Big)$ by definition of Λ_n. Thus,

$$L_0\Big(\theta_n^*, P_n^*; \Pi_0\Big) > L_n\Big(\theta_n^*, P_n^*; \widehat{\Pi}\Big) - \frac{\tau}{2} \geq L_n\Big(\theta, P_n^*; \widehat{\Pi}\Big) - \frac{\tau}{2} > L_0\Big(\theta, P_n^*; \Pi_0\Big) - \tau$$

for any $\theta \in \Theta$. Therefore,

$$\begin{aligned}
A_n \;&\Rightarrow\; \Big\{L_0\Big(\theta_n^*, P_n^*; \Pi_0\Big) > L_0\Big(\theta, P_n^*; \Pi_0\Big) - \tau, \forall\theta \in \Theta\Big\},\\
&\Rightarrow\; \Big\{L_0\Big(\theta_n^*, P_n^*; \Pi_0\Big) > \max_{\theta\in\Theta} L_0\Big(\theta, P_n^*; \Pi_0\Big) - \tau\Big\},\\
&\Rightarrow\; \Big\{\tau > T\Big(\theta_n^*, P_n^*; \Pi_0\Big)\Big\},\\
&\Rightarrow\; \Big\{\min_{(\theta,P)\in B_\epsilon^c(\theta_0;P^0)\cap\mathcal{E}} T(\theta, P; \Pi_0) > T\Big(\theta_n^*, P_n^*; \Pi_0\Big)\Big\} \text{ by (12)},\\
&\Rightarrow\; \Big\{(\theta_n^*, P_n^*) \in B_\epsilon(\theta_0, P^0)\Big\}.
\end{aligned}$$

The last induction uses the fact that $(\theta_n^*, P_n^*) \in \mathcal{E}$. Therefore, $\Pr(A_n) \leq \Pr\Big((\theta_n^*, P_n^*) \in$

$B_\epsilon(\theta_0; P^0)\big)$. By the uniform convergence of $L_n(\cdot; \widehat{\Pi})$ to $L_0(\cdot)$, $\Pr(A_n) \to 1$ as $n \to \infty$. Thus,

$$\Pr\Big((\theta_n^*, P_n^*) \in B_\epsilon(\theta_0; P^0)\Big) \to 1. \tag{13}$$

For the case in which Λ_0 is a singleton, this suffices for consistency of $\widehat{\theta}_{2SNPL}$.

In the general case in which Λ_0 has multiple elements, the proof follows from the same arguments in Aguirregabiria and Mira (2007), who proceed by showing the following results sequentially: (1) ϕ_n converges to ϕ_0 in probability uniformly in a neighborhood around P^0; (2) with probability approaching 1, there exists an element (θ_n^*, P_n^*) of Λ_n in any open ball around (θ_0, P^0); and (3) with probability approaching 1, the 2SNPL estimator is the element of Λ_n that belongs to an open ball around (θ_0, P^0).

(Asymptotic Normality of $\widehat{\theta}_{2SNPL}$) We now derive the limit distribution of $\widehat{\theta}_{2SNPL}$. To simplify notation, we drop the subscript $_{2SNPL}$ from the notation of this estimator in the proof below. By definition,

$$\frac{1}{n}\sum\nolimits_{i=1}^{n} \nabla_\theta l_i(\hat{\theta}, \hat{P}; \widehat{\Pi}) = 0 \text{ and } \hat{P} - \Gamma(\hat{\theta}, \hat{P}; \widehat{\Pi}) = 0.$$

A stochastic mean value theorem between $(\theta_0, P^0; \Pi_0)$ and $(\hat{\theta}, \hat{P}; \widehat{\Pi})$, together with consistency of $(\hat{\theta}, \hat{P})$ and $\widehat{\Pi}$, implies that

$$\begin{aligned} \frac{1}{\sqrt{n}}\sum_{i=1}^{n} s_{\theta,i} - \Omega_{\theta\theta}\sqrt{n}\left(\hat{\theta} - \theta_0\right) - \Omega_{\theta P}\sqrt{n}\left(\hat{P} - P^0\right) - \Omega_{\theta\Pi}\sqrt{n}\left(\widehat{\Pi} - \Pi_0\right) &= o_p(1), \\ \left(I - \Gamma_P^0\right)\sqrt{n}(\hat{P} - P^0) - \Gamma_\theta^0\sqrt{n}(\hat{\theta} - \theta_0) - \Gamma_\Pi^0\sqrt{n}(\widehat{\Pi} - \Pi_0) &= o_p(1). \end{aligned}$$

Solving for $\sqrt{n}(\hat{P} - P^0)$ from the second set of equations and substituting into the first set, we get

$$\begin{aligned} &\underbrace{[\Omega_{\theta\theta} + \Omega_{\theta P}(I - \Gamma_P^0)^{-1}\Gamma_\theta^0]}_{\equiv M}\sqrt{n}(\hat{\theta} - \theta_0) \\ = \;& \frac{1}{\sqrt{n}}\sum_{i=1}^{n} s_{\theta,i} - [\Omega_{\theta P}(I - \Gamma_P^0)^{-1}\Gamma_\Pi^0 + \Omega_{\theta\Pi}]\sqrt{n}(\hat{\Pi} - \Pi_0) + o_p(1) \\ = \;& \frac{1}{\sqrt{n}}\sum_{i=1}^{n} \underbrace{\left\{s_{\theta,i} - [\Omega_{\theta P}(I - \Gamma_P^0)^{-1}\Gamma_\Pi^0 + \Omega_{\theta\Pi}]r_{0,i}\right\}}_{\equiv \tilde{s}_i} + o_p(1), \end{aligned}$$

where the second equality uses the asymptotic linear representation of $\sqrt{n}(\widehat{\Pi} - \Pi_0)$ and its influence function $r_{0,i} \equiv r_i(\Pi_0)$. The asymptotic distribution of $\hat{\theta}$ then follows from the continuous mapping theorem.

□

Appendix B Monte Carlo Evidence

In this appendix, we illustrate the finite-sample performance of our 2SNPL estimator by several Monte Carlo experiments. We consider four players in the game, each associated with X_1 and X_2, which are drawn from the bivariate normal distribution with mean zero, unit variance, and covariances 0.5. A pair of independent standard normal variates (v, η) were drawn. We consider two cases: homogeneous competitive effects and heterogeneous competitive effects.

B.1 Homogeneous competitive effects

Consider a game with four players indexed by $k = 1, 2, 3, 4$. We generate the error term as $u_k = \lambda v_k + \eta_k$ and the endogenous variable as

$$X_{k2} = \pi_0 + \pi_1 X_{k1} + \pi_2 Z_k + v_k.$$

Let (X_{k1}, Z_k)'s be drawn from bivariate normal distribution with mean $(0, 0)$ and variance-covariance matrix $\begin{pmatrix} 1 & 0.5 \\ 0.5 & 1 \end{pmatrix}$. We set the true parameter $(\pi_0, \pi_1, \pi_2, \lambda) = (1, 1, 1, 1)$. The conditional choice probabilities $P^0 = (P_1^*, P_2^*, P_3^*, P_4^*)$ in the BNE are solved by

$$P_k^* = \Phi\Big(\beta_0 + \beta_1 X_{k1} + \gamma X_{k2} + \alpha \sum_{j \neq k} P_j^* + \lambda v_k\Big), k = 1, 2, 3, 4.$$

The decisions are then generated by

$$Y_k = 1\Big\{\beta_0 + \beta_1 X_{k1} + \gamma X_{k2} + \alpha \sum_{j \neq k} P_j^* + u_k > 0\Big\}, k = 1, 2, 3, 4.$$

We set the true parameter $(\beta_0, \beta_1, \gamma, \alpha) = (1, 1, 1, -0.5)$. Each simulation was based on a random sample of (200,400,800) observations and was replicated 1000 times. We report the average biases and the mean squared errors for true parameter $(\beta_0, \beta_1, \gamma, \lambda, \alpha) = (1, 1, 1, 1, -0.5)$ in Table 1.

B.2 Heterogeneous competitive effects

We now consider Monte Carlo designs in which the competition effects differ across "strong" and "weak" players. All other settings are the same as in the homogeneous case, except that the conditional choice probabilities $P^0 = (P_1^*, P_2^*, P_3^*, P_4^*)$ in BNE are

Table 6: Homogeneous Competitive Effects

	Average Bias				
n	β		γ	λ	α
200	0.042	0.027	0.016	-0.021	0.019
400	0.010	0.009	0.015	-0.006	0.012
800	0.008	0.010	0.003	-0.002	0.007
	Mean Squared Error				
n	β		γ	λ	α
200	0.102	0.040	0.017	0.021	0.024
400	0.048	0.018	0.009	0.011	0.011
800	0.023	0.010	0.004	0.005	0.006

Table 7: Heterogeneous Competitive Effects

	Average Bias					
n	β		γ	λ	α	
200	0.021	0.024	0.028	0.028	-0.010	-0.029
400	0.013	0.016	0.012	0.015	-0.005	-0.015
800	0.000	0.008	0.010	0.006	-0.001	-0.008
	Mean Squared Error					
n	β		γ	λ	α	
200	0.090	0.039	0.017	0.023	0.025	0.024
400	0.041	0.018	0.009	0.011	0.011	0.010
800	0.022	0.009	0.004	0.006	0.006	0.005

solved by

$$P_k^* = \Phi\Big(\beta_0 + \beta_1 X_{k1} + \gamma X_{k2} + \alpha_k \sum_{j\neq k} P_j^* + \lambda v_k\Big), k = 1,2,3,4,$$

where $\alpha_1, \alpha_2 = \alpha_S$ and $\alpha_3, \alpha_4 = \alpha_W$.[45]

The decisions are then generated by

$$Y_k = 1\Big\{\beta_0 + \beta_1 X_{k1} + \gamma X_{k2} + \alpha_k \sum_{j\neq k} P_j^* + u_k > 0\Big\}, k = 1,2,3,4,$$

where we have the true parameter $(\alpha_S, \alpha_W) = (-0.5, -1)$. Each simulation is based on a random sample of (200,400,800) observations and is replicated 1000 times. We report the average biases and the mean squared errors for $(\beta_0, \beta_1, \gamma, \lambda, \alpha_S, \alpha_W)$ with true values $(1, 1, 1, 1, -0.5, -1)$ in Table 2.

[45] In this example, we take the first two players as strong and the rest two players as weak. The labels for heterogeneous competition effects indicates what type of these players are, not the type of competitors they will face after entry.

Both Tables 1 and 2 show that our estimator converges to the true parameter values at the parametric root-n rate. In both cases, the variances of the estimators seem to be the dominating component in the mean-squared error (relative to bias).

Appendix C Cellular Network Explained

A cellphone is a portable telephone that can make and receive calls over a radio frequency ("spectrum") while the user is moving within a service area. When a user makes a phone call or sends a message, her cellphone converts her voice or message into electrical signals, which are transmitted from her location to the nearest cell tower via radio waves. The network of cell towers then relays the radio waves to the receiver's cellphone, which converts it to electrical signals and then back to sound, text, or image again. In this process, data travel in a "cellular network," which is composed of cellphones, base transceiver stations ("cell sites"), mobile telephone switching offices, and the public switched telephone network. A cellphone is a type of Mobile Subscriber Unit, which consists of a control unit and a transceiver that transmits and receives radio transmissions to and from a cell site. The term cell site refers to the physical location of radio equipment that provides coverage within a cell. The hardware located at a cell site includes power sources, interface equipment, radio frequency transmitters and receivers, and antenna systems. A mobile telephone switching office is the central office for mobile switching. It houses the mobile switching center, field monitoring, and relay stations for switching calls from cell sites to wire-line central offices. The public switched telephone network is made up of local networks, exchange area networks, and the long-haul network that interconnect telephones and other communication devices on a worldwide basis. Boccuzzi(2019) describes the basics of cellular communications.

A new generation of network technology has arrived in almost every decade since the inception of such technology. The first two generations (0G and 1G) were before the widespread use of cellphones.[46] In the 1990s, 2G started the use of digital transmission instead of analog transmission, marking the start of widespread use of cellphones in our lives. In the 2000s, 3G was the predominant technology, and in the 2010s, it was 4G-LTE. Now we are facing the transformation from 4G-LTE to 5G, the newest generation of network technology.

[46] 0G refers to pre-cellphone mobile technology, such as radio telephones that were placed in cars before the advent of cellphones. 1G refers to Analog Cellular Networks, which employ multiple cell sites to transfer calls from one site to the next as the user travels between cell sites during a conversation.

Appendix D Robustness of Table 3

We check the robustness of our Table 3's results by: 1) restricting our analysis to homogeneous competition effects; 2) using any generation of technology (2G, 3G, and 4G non-LTE combined) instead of just 3G to measure a firm's previous network investment in the focal market; 3) using a firm's 4G deployment in neighboring markets in 2015, instead of that in 2018, to measure the firm's network investment in neighboring markets.

Table 8 reports the results from these alternative specifications. In specification (1), the Big Four are treated as equal competitors. Results in this specification are very close to specification (1) in Table 3, suggesting only small differences in how AT&T/Verizon and T-Mobile/Sprint reacted to expected competition. In specification (2), for $X_{2,1}$, we expand from 3G to include any previous generation of technology deployment in the focal market. Compared with specification (1) in Table 3, the main change is that the estimate of the coefficient for V_1 and for $X_{2,1}$ become smaller in their absolute values. In specification (3), we do not consider the concurrent deployment of 4G-LTE in the neighboring census tracts; instead, we restrict 4G-LTE deployment in the neighboring census tracts to the status quo before the start of the entry game. Compared with specification (1) in Table 3, the main change is that the estimate of the coefficient for V_2 and for $X_{2,2}$ become smaller in their absolute values. The competition effects in specification (3) also become much smaller. In specifications (2) and (3) of Table 8, the qualitative results stay the same as Table 3.

In summary, these alternative specifications often produce marginally different magnitudes in estimates, but they all point to the importance of the network investment effect, as well as a consistently negative expected competition effect.

Appendix E First-stage Results

Table 9 reports the first-stage regression results for the endogenous network investment model. In the reported results in this paper, we adopt a specification with covariates of X_1, Z, and their squared terms in the first stage regressions of $X_{2,1}$ and $X_{2,2}$. We reported the first-stage results in Spec. (2), corresponding to columns (2) and (4) in Table 9. In Spec. (2), the adjusted R^2's for $X_{2,1}$ and $X_{2,2}$ regressions are 0.077 and 0.333, respectively. In Spec. (1), we report the first-stage results in which we include only

Table 8: Robustness of Table 3

	Homogeneous Competition		Use any G for $X_{2,1}$		Use 2015's 4G for $X_{2,2}$	
	(1)		(2)		(3)	
Variable	Est.	S.E.	Est.	S.E.	Est.	S.E.
Pop (in 000's)	0.078***	0.020	0.071***	0.015	0.051***	0.015
% Female	0.436	0.758	0.711	0.520	0.399	0.520
% Senior	-1.046**	0.413	-0.954***	0.338	-0.772**	0.338
% White	-0.224	0.513	-0.235	0.395	-0.471	0.395
% Black	-0.351	0.527	-0.359	0.413	-0.728*	0.413
% Native	-1.391***	0.537	-1.626***	0.398	-1.045***	0.398
% Asian	0.877	1.314	1.181	1.036	0.310	1.036
% Hispanic	-0.468	0.340	0.042	0.232	-0.467**	0.232
% College	-0.155	0.402	0.103	0.320	0.180	0.320
% Labor force	-0.943***	0.321	-0.846***	0.243	-1.108***	0.243
% Work home	0.277	0.521	0.733*	0.430	0.051	0.430
% Long commute	0.070	0.307	-0.144	0.217	0.439**	0.217
HH income	-0.002	0.003	-0.006**	0.002	0.001	0.002
HH size	-0.042	0.026	-0.043**	0.019	-0.013	0.019
Pop density	-0.132	0.089	-0.192***	0.070	-0.051	0.070
% Rural	0.221*	0.126	0.021	0.074	00.116	0.074
Mostly Water	-1.858***	0.548	-2.438***	0.410	-1.383***	0.410
# Incumbents	-0.162***	0.043	-0.188***	0.034	-0.007	0.034
Intercept	0.926	0.784	1.256**	0.540	0.670	0.540
Network Investment Effects						
$X_{2,1}$	3.743***	0.788	1.261***	0.235	3.705***	0.235
$X_{2,2}$	1.610***	0.322	1.958***	0.119	0.254**	0.119
V_1	-1.731**	0.783	0.704***	0.183	1.103***	0.183
V_2	1.531***	0.335	1.114***	0.204	0.472**	0.204
Competition Effects						
Any P.E.	-1.099***	0.062	-	-	-	-
Strong P.E.	-	-	-1.012***	0.084	-0.436***	0.084
Weak P.E.	-	-	-1.086***	0.064	-0.352***	0.064

Notes: The results are based on 6,244 observations, corresponding to two to four potential entrants for 2,582 Census tracts. Standard errors are obtained from resampling of markets with replacement 1,000 times). Asterisks indicate the statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

(X_1, Z) — but not the squared terms — as the regressors.

Table 9: First Stage Regressions with Different Specifications

	$X_{2,1}$		$X_{2,2}$	
Variable	Spec.(1)	Spec.(2)	Spec.(1)	Spec.(2)
Pop (in 000's)	0.001	0.024**	-0.002	0.009
% Female	0.075	0.086	0.157	0.081
% Senior	0.009	0.269	0.126**	0.171
% White	0.105	0.122	-0.394**	0.340
% Black	0.047	0.054	-0.192	-0.127
% Native	0.010	0.012	-0.179*	-0.160
% Asian	-0.231	-0.739**	-0.433**	-0.229
% Hispanic	0.160***	0.277**	-0.091	-0.120
% College	0.109	0.222	0.123*	-0.422**
% Labor force	-0.140**	-0.578**	-0.341***	-0.883***
% Work home	-0.014	0.084	-0.327***	-0.744***
% Long comm.	-0.014	-0.198	0.342***	0.396***
HH income	-0.001**	-0.002**	0.000	0.001
HH size	0.000	0.016	0.011***	0.016
Pop density	-0.005	0.001	-0.011	0.002
% Rural	-0.098***	0.003	-0.080***	-0.111
Mostly water	-0.235***	-0.184***	0.066	0.083
# Incumbents	-0.017***	-0.076***	0.021***	0.026
Lagged Pop (in 000's)	0.003	0.049*	0.030***	0.023
Lagged % Female	0.203	4.858	0.416	1.851
Lagged % Senior	0.265**	0.164	0.212*	-0.102
Lagged % White	0.544***	0.257	0.135	0.394
Lagged % Black	-0.392**	-0.883**	-0.061	-0.983***
Lagged % Native	-0.556***	-0.731**	-0.179	-0.844**
Lagged % Asian	-0.338	0.998	-0.331	-0.293
Lagged % Hispanic	-0.050	0.043	0.109	-0.502**
Lagged % College	0.069	-0.294	0.143	-0.825***
Lagged % Labor force	0.089	-0.062	-0.177*	3.387***
Lagged % Work home	0.200	-0.018	-0.225	-1.153**
Lagged % Long comm.	0.078	0.223	-0.022	0.447**
Lagged HH income	0.001**	0.010***	0.003***	0.025***
Lagged HH size	0.011	0.030	0.014	0.046**
Lagged Pop density	-0.006	0.002	0.014	0.054***
Lagged % Rural	0.007	0.204**	-0.151***	0.277***
Lagged Mostly water	-0.496***	-0.780***	-0.591***	-1.023***
Intercept	0.408*	-1.385	0.329	-1.597
Including squared terms	No	Yes	No	Yes
# of Regressors	35	69	35	69
Adjusted R^2	0.068	0.077	0.306	0.333

Notes: To save space, we only report estimates for (X_1, Z) in specification (2).