

A Game of Quality Competition Among ISPs *

Andrew Kearns [†]

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Abstract

I examine the extent to which competition among Internet service providers (ISPs) affects the availability and quality of broadband. I develop a structural model of competition based on the empirical games literature in which ISPs vertically differentiate on the basis of transmission technology and estimate the game using geographic deployment data from the FCC. Because providers' entry and product quality decisions are endogenous to their competitors' choices, the structural model allows me to properly identify the effect of competition while accounting for strategic behavior. Utilizing data on providers' past deployment, I am also able to identify the fixed costs associated with entry and product quality adjustments. My results indicate that firms are more likely to enter and offer high speed service in larger, denser, and wealthier markets, firms tend not to differentiate within markets, and fixed costs of entry are large. I also find that firm heterogeneity is important for explaining ISPs' entry patterns. I use the parameter estimates of the game to determine the effect of competition on firms' incentives to increase availability and quality. Specifically, I conduct counterfactual simulations in which I vary the degree of competition and the size of entry costs. I find (1) if providers behaved as monopolists, on average they would slightly increase quality, and (2) large reductions in entry costs are required to induce firms to substantially increase quality.

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[†]Department of Economics, Northeastern University, email: kearns.an@northeastern.edu. Thank you to James Dana, John Kwoka, and Imke Reimers for many helpful comments and suggestions.

1. Introduction

Promoting widespread access to affordable high-quality Internet service is a major public policy issue in the United States. Since the founding of the Federal Communications Commission in 1934, one of the organization’s fundamental objectives has been to achieve universal service: “to make available, so far as possible, [...] world-wide wire and radio communication service with adequate facilities at reasonable charges.”¹ The passage of the 1996 Telecommunications Act reaffirmed this objective mandating that “[q]uality services should be available at just, reasonable, and affordable rates” and “[a]ccess to advanced telecommunications and information services should be provided in all regions of the Nation.”² At the time the agency was established, the principle of universal service was applied to the propagation of telephone service; in the past two decades the same principle has been reapplied to the deployment of broadband service. With the advent of the Internet, the importance of access to telecommunication services for the success of both individuals and businesses in the modern economy has become increasingly apparent. As a result, the state of the broadband market has attracted the attention of policymakers, even outside of the telecommunications industry. In particular, policymakers across the political spectrum worry that lack of Internet access can exacerbate inequality of opportunity for poor and rural populations, a problem dubbed “the Digital Divide.”³

In recent years, the FCC has made closing the Digital Divide, particularly in rural and Tribal areas, a policy priority. According to the Commission’s 2018 broadband deployment report, “[f]ar too many Americans remain unable to access high-speed broadband Internet access, and we have much work to do if we are going to continue to encourage the deployment of broadband to all Americans, including those in rural areas, those on Tribal lands, and those in schools and classrooms.”⁴ However, even in urban areas where broadband access is most widespread, competition is still relatively limited. In most markets, “the typical American has a choice of only two fixed-line broadband providers: the local telephone company and the local cable company.”⁵ In addition to the issue of access, consumers and policymakers alike are concerned about the quality of broadband service:

Fast internet service is crucial to the modern economy, and closing the digital divide is seen as a step toward shrinking the persistent gaps in economic opportunity, educational achievement and health outcomes in America. In some areas with spotty or no service, children do their homework in Wi-Fi-equipped buses or fast-food restaurants, small businesses drive to internet hot spots to send sales pitches and medical records are transported by hand on thumb-drive memory sticks.

– The New York Times⁶

Counties without modern internet connections can’t attract new firms, and their isolation discourages the enterprises they have: ranchers who want to buy and sell cattle in online auctions or farmers who could use the internet to monitor crops. Reliance on broadband includes any business that uses high-speed data transmission, spanning banks to insurance firms to factories.

– The Wall Street Journal⁷

¹Communications Act of 1934, 47 U.S.C. §151.

²*Id.*, 47 U.S.C. §254.

³FCC Website, <https://www.fcc.gov/about-fcc/fcc-initiatives/bridging-digital-divide-all-americans>

⁴FCC 2018 Broadband Deployment Report, at page 6.

⁵Nuechterlein, J. E. and Weiser, P. J. (2013): *Digital Crossroads* (2nd Edition), MIT Press, at page 22.

⁶Lohr S., “Digital Divide Is Wider Than We Think, Study Says,” *The New York Times*, December 4, 2018.

⁷Levitz J. and Bauerlein V., “Rural America is Stranded in the Dial-Up Age,” *The Wall Street Journal*, June 15, 2017.

At the moment there is relatively little empirical evidence about the effect of competition among ISPs on service quality, however, understanding the extent to which competition affects both the availability and quality of broadband is key to designing effective public policy aimed at encouraging the widespread provision of affordable, high speed Internet service. To that end, I study how competitive pressure affects ISPs' local entry and product quality decisions in Atlanta, a mature urban market with several competitors, where it may be possible to observe the effects of competition. The goal of my analysis is to produce a realistic model of ISPs' competitive behavior that I can test with data, as well as use to determine how competition affects the availability and quality of broadband service in Atlanta. Specifically, I use data from the FCC's Form 477 survey of broadband providers to estimate a static game of ISPs' entry and quality decisions. Then I simulate how direct and indirect changes in the degree of competition affect firms' entry and quality choices. Because I rely solely on providers' entry and quality decisions to draw inferences about supply and demand conditions, this approach limits my ability to draw conclusions about how changes in market structure affects consumer welfare, but it does allow me to investigate how changes in competition affect quality. Below I give a brief overview of the model, estimation strategy, and my preliminary results.

Often in the empirical Industrial Organization literature, researchers are unable to obtain detailed price and quantity data for a particular industry but are able to observe the number of firms operating in different geographic markets. Similarly, in this paper I have rich geographic data on ISPs' footprints, as well as information about the quality of broadband they provide in different markets, but am unable to observe prices and quantities. Therefore, in order to draw inferences about the relationship between competition and quality using only information on deployment and quality, I develop a structural model in which ISPs' entry and quality decisions depend upon common market characteristics and the choices of their competitors, in the tradition of the estimation of entry games in IO (Berry and Reiss 2007). I also exploit data on firms' past choices, which allows me to identify the fixed cost parameters associated with entry and quality adjustments without estimating a fully dynamic model (though my static model may underestimate these parameters). Additionally, due to the large variation in observed entry patterns across firms, I allow for provider-specific payoffs.

In my empirical analysis, I pay particular attention to carefully categorizing broadband service into quality tiers based on providers' technologies of transmission and download speeds. I also try to choose a relatively small set of market characteristics that capture the fundamental economic factors which explain ISPs' entry and investment behavior. The estimates of the game appear to be economically sensible. First, consistent with large economies of scale and density in the telecommunications industry, all else equal ISPs are more likely to enter larger, denser markets with a higher level of per capita income. Additionally, providers are more likely to offer high quality service in more populated, denser, and wealthier markets. Second, as expected competition has a negative impact on providers' payoffs, however, unexpectedly the pattern of competitive effects suggests that firms tend not to vertically differentiate within markets; further empirical investigation is needed to corroborate this result. Third, fixed costs associated with entry are relatively large and even larger for high quality service providers, fixed costs of adjusting quality are also significant, and the cost of entry is lower in neighboring markets. Forth, firm heterogeneity explains a lot of the variation in providers' entry and quality choices.

Finally, because it isn't possible to infer the relationship between competition and quality from the parameter estimates of the game alone, I conduct two counterfactual experiments to determine how changes in the degree of competition affect providers' decisions in equilibrium. In the first, I simulate providers'

entry and quality choices as if they behaved as monopolists. In the second, I gradually increase competitive pressure by reducing the cost of entry for high quality providers. My preliminary results show that in the absence of competition, providers increase high quality deployment, and that significant reductions in entry costs are necessary to induce meaningful increases in the deployment of high quality service. Also, because providers have heterogenous payoffs, changes in providers' equilibrium strategies vary substantially.

2. Related Literature

2.1 Oligopoly Theory

A major challenge for my empirical analysis is cleanly identifying the effect of competition on firms' entry and quality decisions. Oligopoly theory has shown that the causal relationship between competition and quality is quite complex and sensitive to market structure. While economists generally believe competition incentivizes firms to produce higher quality products, theory has produced mixed results. For example, Aghion, Bloom, Griffith, and Howitt (2005) analyze a model that implies an inverted U-shaped relationship between competition and innovation, suggesting that an optimal level of competition may exist to maximize firms' innovation incentives. However, Vives (2008) shows that the theoretical relationship between competition and innovation may be more ambiguous than economists previously understood and may depend substantially on market structure. If this is the case, then targeted empirical studies are necessary to determine the relationship between competition and quality in specific industries. Unfortunately, empirically identifying the degree to which competition matters is challenging for several reasons:

(1) Identification is confounded by market structure endogeneity. Sutton's (1991) early work on the importance of market structure demonstrates that a firm's entry and product quality decisions depend upon its rivals' choices, which affect the degree (or toughness) of competition in the market and thus the firm's expected profits. Therefore, a model that attempts to explain the relationship between competition and quality should simultaneously account for all potential entrants' entry and product quality decisions or, as discussed in Vives (2008), should rely upon some source of exogenous variation in market structure.

(2) Measuring the degree of competition is further complicated when firms are heterogenous. Specifying a model in which firms are homogenous is often convenient but may fail to capture the realities of the industry.

(3) Static economic models may not adequately explain firms' decision making behavior with respect to quality, because we might expect firms to engage in quality competition over the long-run, while focusing on price (or quantity) competition in the short-run. Therefore, it may be necessary to incorporate dynamics in order to more accurately describe firm behavior.

(4) In many industries, product quality is multi-dimensional and these dimensions may be difficult to measure objectively. Furthermore, important product characteristics may be unobserved by the analyst.

(5) Firms can offer a menu of products with varying quality in order to increase profits through price discrimination, and the effect of price discrimination on competition is ambiguous in oligopoly markets.

In an attempt to address most of these concerns, I estimate a static entry game of incomplete information in which firms engage in vertical differentiation to determine the extent to which competition among urban

ISPs affects their local entry behavior. This structural approach allows me to explicitly address (1) market structure endogeneity, which can be challenging to account for with reduced-form econometric methods. I also allow firms' payoffs to be heterogeneous and depend on past choices (states), to account for (2) differences across firms and (3) dynamic behavior. Finally, I study an industry in which product quality is well-defined (4). While consumer demand for broadband is not solely determined by downstream speed (price, upstream speed and connection reliability are of course also important), downstream speed is perhaps most important dimension of broadband quality and is an objective measure of quality, which makes the market for broadband a suitable lens through which study the interaction between competition and quality.

2.2 Telecommunications

This paper adds to a small but growing literature analyzing firm entry and quality in the broadband market, as well as a broader literature on entry in the telecommunications industry. My analysis is most closely related, to Augereau, Greenstein and Rysman (2006) who model ISPs' decisions to adopt 56K modems in a static game of incomplete information using data from the late 1990s. Similar to this study, they analyze ISPs' decisions to increase the speed of their modems from 33K to 56K across geographic markets. However, in their application ISPs' strategies to adopt faster modems also reflect the incentive to either coordinate or differentiate on a technological standard, since two incompatible modem technologies were vying to become the industry standard at the time. Based on their analysis it appears that ISPs tended not to coordinate on a standard technology in order to retain temporary market power. Unlike this study, they do not model firms' entry and upgrade decisions simultaneously, instead ignoring the possibility of entry.

Two other closely related studies are Fister (2018) and Molner and Savage (2017) both of which estimate reduced-form relationships between ISP competition and quality while correcting for market structure endogeneity. Like this paper, Fister (2018) studies the broadband market using geographic data on wireline providers from FCC Form 477. She analyzes the effect of entry on incumbents' choices of transmission technology, downstream bandwidth, and deployment using an instrumental variable approach to correct for endogenous entry. She finds entry incentivizes incumbents to increase quality (both technology of transmission and downstream bandwidth) and market coverage.

Similarly, Molner and Savage (2017) estimate the relationship between the number of wireline and wireless competitors and average downstream and upstream speeds using data on geographic markets. However, they use a different two-stage approach to deal with market structure endogeneity. First, they estimate entry models based on Breshnahan and Reiss (1991) for wireline and wireless providers, then they regress average market bandwidth on the number of competitors using expected profits from the first-stage as control variables. They too find a positive (concave) relationship between competition and quality, and additionally find that competition from wireless providers does not have a significant impact on the quality of wireline providers. Both papers find that OLS estimates understate the effect of competition on quality, highlighting the importance of correcting for market structure endogeneity.

Other notable papers that have studied the competitive behavior of ISPs include Augereau and Greenstein (2001), Wallsten and Mallahan (2010), and Xiao and Orazem (2011). Several other papers have studied the effects of competition on entry, quality, and consumer welfare in local telephone markets: Greenstein and Mazzeo (2006), Economides, Seim, and Vivard (2008), Seim and Vivard (2011), Goldfarb and Xiao (2011), and Fan and Xiao (2015). This literature is also relevant given the structural similarities between

local telephone and broadband markets.

Finally from a methodological perspective, this paper builds on the literature of the estimation of static entry games without price and quantity data. In particular, the game I estimate draws on elements from Seim (2006), Mazzeo (2002), and Lin (2015), each of which specify an entry game that allows for endogenous product differentiation.

3. Industry Background

The dominant players in today’s broadband market are legacy telephone providers, such as AT&T and Verizon, and cable providers, such as Comcast and Charter. The current state of competition in the market is largely the result of interaction between three fundamental forces: (1) technology, (2) economics, and (3) past regulation. While the modern telecommunications sector is mostly deregulated, the evolution of the market over the past two decades depends upon conditions established under the pre-1996 regulatory regime.

Before the deregulation of the industry following the 1996 Telecommunications Act, the prevailing wisdom held that local telephone markets were natural monopolies, and in an effort to achieve universal service, the government granted monopoly rights to local telephone companies to encourage the deployment of networks across the United States. The logic for granting monopoly rights was reasonable given the technology and economics of the industry at the time, namely the high fixed cost of building copper wire networks, low and rapidly decreasing marginal cost of providing telephone service, and network effects (the characteristic that a consumer’s valuation of telephone service depended upon the number of other subscribers to the same network). Due to enormous economies of scale and density, as well as network effects, there was little incentive for a potential competitor to challenge an incumbent, and therefore regulating the local monopolists was logical. Until deregulation these legacy carriers were largely insulated from local competition, and because of their “head start,” legacy telephone companies continue to enjoy a competitive advantage over their rivals.

Over time, however, as Nuechterlein and Weiser (2013) explain, technological convergence in telecommunications created the opportunity for companies that had historically provided distinct services in different areas of the industry the ability to compete with one another in the provision of broadband. For example, in today’s market legacy telephone providers and cable companies that previously offered distinct products (telephone and television) though specific channels now compete with one another in the provision of data, which typically consists of a bundle of Internet, television, and voice services. At the same time, particularly in high density urban markets, high demand for these services, in combination with technological convergence, has created an opportunity for new entrants to challenge incumbents disrupting the natural monopoly paradigm. In urban markets especially, it’s now possible for some potential entrants to siphon off an incumbent’s subscribers by competing on price and quality despite the high cost of network infrastructure.

With respect to the supply of ISPs, technology and economies of scale and density continue to shape the market for broadband. Despite technological advancements in the provision of wireless Internet service, fixed wireline service is still superior in terms of quality, and so most households have continued to rely upon fixed wireline service as their main Internet connection where possible.⁸ As a result of consumers’

⁸Nuechterlein and Weiser (2013) suggest that substitution for wireline and wireless Internet service is likely to become an

continued reliance upon wireline service, economies of scale and density driven by the large fixed cost of deploying wireline networks are still important economic factors. On the other hand, with the emergence of the Internet the importance of networks effects has dwindled, because the content a consumer chooses to access online does not depend on his or her service provider.

While the dissipation of network effects has somewhat reduced barriers to entry, the number of competing ISPs is still relatively few even in urban markets. For example, Atlanta is, for the most part, dominated by two large providers AT&T and Comcast, which face competition from two medium sized providers Charter and Windstream in certain areas of the city. Several other providers including Google Fiber and WideOpenWest also operate in the city but with a much smaller presence. Thus while Atlanta departs from the typical local telco/cable duopoly, the fundamental technological, economic, and historical regulatory forces discussed above still govern the competitive landscape.

Given the aforementioned characteristics of the modern broadband market, the economic model I develop assumes that market size and density are the most important (non-strategic) factors that affect firms' entry and quality decisions. Also, given the fundamental differences between providers in terms of technology and historical advantages, I incorporate firm heterogeneity.

4. Data Description

My three main sources of data are ISP deployment data from FCC Form 477,⁹ market demographic data from the Census Bureau's American Community Survey,¹⁰ and geographic census block data from TIGER/Line. I collate data from these three sources to create a dataset containing ISP entry and product quality decisions, as well as demographic characteristics by block group for the years 2014 to 2018. I discuss the integration of these data sources and Atlanta's broadband market in more detail below.

4.1 ISP Data

Every six months, the FCC requires that major telecommunications providers file Form 477 in which firms identify the census blocks in which they are currently deployed, including information about the type of service they provide in each block.¹¹ ISPs report the following information for each census block in which they provide service: 15-digit census block code, Holding Company Name (the provider's parent company), DBA Name (the provider's "doing business as" name e.g. "Comcast"), a technology code (indicating technology of transmission e.g. DSL, cable, fiber), a consumer indicator (denoting whether the provider offers consumer, "mass market" service), maximum advertised downstream bandwidth (consumer grade service speed in mbps), maximum advertised upstream bandwidth (consumer grade service speed in mbps) and a business/government indicator (denoting whether the provider offers business grade service).¹²

increasingly important area of study as wireless technology improves.

⁹FCC Website, "Fixed Broadband Deployment Data from FCC Form 477," https://transition.fcc.gov/form477/FBD/formatting_fbd.pdf

¹⁰American Community Survey 5-Year Data, <https://www.census.gov/data/developers/data-sets/acs-5year.html>

¹¹A provider is considered "deployed" if it serves at least one household in a census block.

¹²FCC Website, "How Should I Format My Fixed Broadband Deployment Data?," https://transition.fcc.gov/form477/FBD/formatting_fbd.pdf

The FCC makes state-by-state Form 477 data available to the public on its website. I collect annual data for the state of Georgia from 2014 to 2018. Then using the Census Bureau’s definition of the Atlanta MSA, I limit the area of my analysis to the census blocks that comprise Atlanta. Additionally, I restrict my sample of providers to those offering consumer grade fixed wireline service (i.e. DSL, cable, and fiber technologies). While competition from fixed wireless and satellite providers may impact the entry and investment decisions of fixed wireline providers, I exclude these providers from my analysis, since fixed wireless and satellite ISPs generally offer inferior service in terms of both quality and price and typically serve rural markets wireline providers have found unprofitable to serve. Furthermore, results from Molnar and Savage (2017) suggest that competition from wireless providers has little impact on wireline providers.

After restricting my sample of providers, I reclassify some as business providers based upon a review of their websites. I also correct some other minor reporting errors in the data.¹³ After limiting my sample to fixed wireline ISPs offering consumer-grade service, I determine that a total of 23 providers served the Atlanta MSA from 2014 to 2018 (see **Table 1**).

Table 1. Number of CBGs Covered by ISPs

Provider	2014	2015	2016	2017	2018
AT&T	2,595	2,596	2,603	2,558	2,536
Access Media 3	3	2	0	1	1
Birch Communications	4	3	2	2	0
Bulldog Cable Georgia	6	0	0	0	0
Charter	653	633	634	673	675
Comcast	2,344	2,351	2,357	2,384	2,393
Cox Communications	1	1	1	1	2
Ellijay Telephone Company	30	30	24	25	25
Frontier	5	5	5	5	5
Google Fiber	0	0	60	113	155
Habersham EMC	0	0	3	2	3
Hargray	0	1	1	1	3
Hotwire	0	12	12	11	13
Mediacom	2	2	2	21	22
One Ring Networks	0	0	0	0	98
Plant Telephone Company	13	13	13	13	13
Public Service Telephone Company	0	0	0	20	24
Sunset (Point Broadband)	0	0	0	0	2
TDS Telecom	19	19	19	20	19
Waverly Hall Telephone	0	0	1	1	0
WideOpenWest (NuLink)	52	53	54	54	54
Windstream	276	694	315	187	233
Yomura Fiber	0	0	0	0	297
Total	6,003	6,415	6,106	6,092	6,573

¹³Some providers offering service in one or two blocks were excluded from the analysis after I determined they were small rural ISPs based in other states.

4.2 Data Aggregation

In order to prepare the data for analysis, I aggregate the census block (CB) level data to the census block group (CBG) level, by determining the highest level of technology and maximum advertised download speed over all CBs within a CBG,

$$tech_m = \max\{tech_i\}_{i=1}^N, \text{ where } N \text{ is the total number of CBs in CBG } m$$

$$speed_m = \max\{speed_i\}_{i=1}^N, \text{ where } N \text{ is the total number of CBs in CBG } m$$

I aggregate the data in this way in order to match data on market characteristics to ISP coverage data. Unfortunately, Census data on annual population, income, and other demographics is only available at the CBG level, therefore I determined that it was appropriate to aggregate the ISP data to the CBG level. While this method of aggregation overstates the highest level of technology and maximum advertised speed for many CBs within a CBG, as well as the degree of competition among ISPs, this methodology is consistent with the FCC’s reporting standards for Form 477, which requests that providers report the highest available downstream speed offered within a CB.

4.3 Market Definition

Here I lay out several assumptions about my data which have implications for my analysis. First, I define a market as a census block group. Unlike other industries, where precise market definition is nebulous due to consumers’ ability to travel to purchase goods, the market for broadband is quite clearly defined, because a household is either served by a particular provider or not; consumers cannot travel to neighbouring block groups to obtain service.¹⁴ Second, I assume that if a provider offers service in a CBG, then it serves all consumers in the CBG, which is consistent with how the FCC analyzes the data. Third, I take providers’ Form 477 submissions at face-value in the sense that they (1) have deployed the technologies of transmission they claim and (2) are in fact capable of delivering the advertised maximum downstream speed they claim. Molnar and Savage (2017) point out that consumers and rival firms have complained that downstream speeds reported in Form 477 data are not representative of speeds consumers experience. Whether consumers who purchase the maximum advertised service actually experience that speed may be less relevant from the provider’s perspective, because each individual consumer’s experience depends upon his/her equipment (modem, router, laptop, etc.), thus an ISP may incur real costs to provide a certain level of quality even if it is “underdelivering” on speed from the consumer’s perspective. Furthermore, I expect advertised quality and actual quality to be positively correlated.

4.4 Atlanta’s Broadband Market

From 2014 to 2018 Atlanta was served by a number of large ISPs which operate in multiple states, as well as by several small providers. The two dominant providers, AT&T and Comcast, consistently served over 2,300

¹⁴However, it should be emphasized that I only observe whether a provider offers service to a single household within a census block. Thus, I know with certainty that a provider does not offer service to any household within a block when I don’t observe the presence of the provider there, but I cannot determine the number of households within a block a provider actually serves.

of the 2,687 census block groups that make up the Atlanta MSA during my sample period (see **Table 1**). Charter and Windstream also covered large sections of the city, followed by Google Fiber, which entered the market in 2016, and WideOpenWest (WOW). Other multi-state providers with a limited presence in Atlanta include Cox, Frontier, Mediacom, and TDS Telecom.

Atlanta’s insulation from significant telecom transactions during the period makes it an ideal candidate to study the local microeconomic behavior of ISPs. Besides the entry of Google Fiber in 2016, the market experienced little disruption despite two major transactions during the period (Frontier’s acquisition of Verizon assets in several markets in 2014 and the Charter/TWC merger in 2015). The only transaction of any significance that affected the market was WideOpenWest’s acquisition of NuLink in 2016. Since WOW did not have a presence in Atlanta before the acquisition, I treat WOW and NuLink as a single provider for purposes of my analysis.

4.5 Provider Speeds, Technologies, and Quality

Between 2014 and 2018 ISPs appear to have invested heavily in network bandwidth (see **Figure 1**). According to FCC Form 477 data, average maximum advertised downstream bandwidth in Atlanta increased over 1,000% during the five year period. Much of this aggregate increase was driven by AT&T and Comcast, however, almost all providers increased their speeds during this period. The FCC’s deployment data reveals that both telco and cable providers upgraded their technologies of transmission enabling them to offer higher higher speeds. For example, in many census blocks AT&T transitioned from DSL (Digital Subscriber Line) service to FTTP (Fiber to the Premises) technology, while Comcast transitioned from DOCSIS (Data Over Cable Service Interface Specification) 3.0 to DOCSIS 3.1. As is shown in **Table 2**, FTTP and DOCSIS 3.1 were significant improvements over their predecessors in terms of increasing the amount of bandwidth ISPs’ could deliver to consumers. Technology upgrades weren’t only implemented by AT&T and Comcast. During the five year period Charter upgraded from DOCSIS 3.0 to DOCSIS 3.1, Windstream started upgrading from DSL to FTTP, and Google Fiber entered the market in 2016 offering FTTP.

Table 2 displays summary statistics by transmission technology for maximum downstream bandwidth from the raw FCC 477 data across all census blocks and consumer grade providers in Atlanta. For purposes of descriptive analysis, I do not correct any likely reporting errors in the data, e.g. copper wire service and DSL cannot deliver speeds up to 1,000 mbps. I report these statistics merely to show that for telco providers there is a clear distinction in quality between low speed service and high speed service by technology – fiber speeds are much faster than other technologies. For cable provider technologies the distinction between low speed and high speed service is slightly less clear, however, comparing the distribution of maximum speeds supported by DOCSIS 3.0 and 3.1, DOCSIS 3.1 is significantly faster than 3.0.

Using transmission technology as a basis for separating broadband service into quality categories, I denote level 1 quality service as “low” quality and level 2 quality service as “high” quality. For telco providers, I consider broadband delivered over copper wire or DSL as level 1 quality service ($q = 1$), while I consider broadband delivered via FTTP as level 2 quality service ($q = 2$). For cable providers, I consider broadband delivered over DOCSIS 1.0, 1.1, 2.0, or 3.0 or another cable modem as level 1 service ($q = 1$), while I consider broadband delivered via DOCSIS 3.1 as level 2 service ($q = 2$). My choice of quality categorization is driven by the bifurcation between transmission technologies in terms of maximum advertised downstream speed I observe in the data. This distinction in quality is the basis of the entry and quality game I estimate.

**Figure 1. Maximum Downstream Bandwidth Over Time
(Standard Box Plots)**

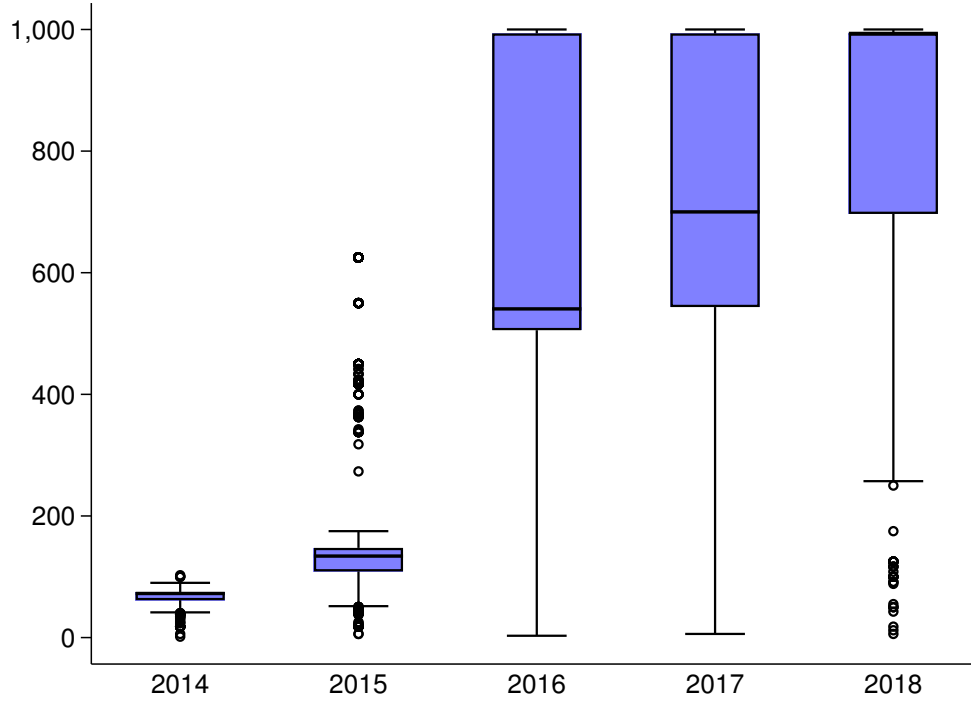


Table 2. Maximum Downstream Bandwidth by Transmission Technology

Transmission Technology	Minimum	5th Per.	25th Per.	Median	75th Per.	95th Per.	Maximum	N
10: Asymmetric xDSL	1	2	3	12	40	100	100	871
11: ADSL2, ADSL2+	1	3	12	18	18	24	50	697
12: VDSL	1	18	24	45	75	100	1,000	6,543
30: Other Copper Wireline	1	2	2	2	2	6	1,000	410
40: Cable Modem other than DOCSIS	30	50	100	100	100	250	250	327
41: Cable Modem - DOCSIS 1, 1.1 or 2.0	6	12	12	12	12	20	20	60
42: Cable Modem - DOCSIS 3.0	12	100	105	250	400	987	987	10,485
43: Cable Modem - DOCSIS 3.1	100	940	987	987	987	987	1,000	4,766
50: Optical Carrier (Fiber TTP)	1	100	1,000	1,000	1,000	1,000	1,000	7,030

5. Estimation Strategy and Economic Model

5.1 Estimation Strategy

My goal is to measure the effect of competition on ISPs' entry and quality decisions controlling for market characteristics. As described above, I have data on firms' entry and quality choices, which vary across geographic markets (CBGs) within the Atlanta MSA, however, I don't observe prices, quantities (subscriptions), or product menus (plans). If I had comprehensive data on ISPs' plans, prices, and subscriptions, then in theory I could estimate demand for broadband, which I could then integrate into a game of incomplete information where each firm chooses a menu of plans to offer in different markets given expected demand. Instead, I rely upon firms' entry and quality decisions, as well as data on market characteristics to identify the effect of competition on providers' choices.

5.2 Model Overview

Following Seim (2006), I model provider behavior as a static entry game with endogenous product differentiation where firms have incomplete information. Unlike Seim's model in which firms (video rental stores) differentiate themselves by choosing where to locate within a market, in my application ISPs differentiate themselves by choosing the quality of broadband to provide to consumers within a market. In both applications, firms differentiate themselves in product characteristic space, however, in the video rental market firms engage in horizontal differentiation, whereas in my application firms engage in vertical differentiation, similar to Mazzeo's (2002) model of entry in the motel industry and Lin's (2015) model of the nursing home industry.

In the game, providers simultaneously choose whether to operate in a market, as well as the quality of broadband to provide to consumers. Each firm maximizes its expected profit, conditional on private information, which depends upon its beliefs about its rivals' choices. An equilibrium in this game is a Bayesian Nash equilibrium (BNE),

$$\mathbb{E}[\pi_{fq}(\cdot)|\epsilon_{fq}] \geq \mathbb{E}[\pi_{fq'}(\cdot)|\epsilon_{fq'}], \forall q' \neq q$$

where firms' private information ϵ_{fq} is an i.i.d. random variable with distribution $G(\cdot)$, which is common knowledge to all providers.

First, I describe a basic entry game without any choice of broadband quality, then I describe the full model incorporating quality choice and firms' states. For brevity, I describe both models in terms of two competing firms, however, the models are easily generalized to N firms and I estimate each model using data on the five largest (by census block group count) providers in Atlanta: AT&T, Comcast, Charter, Windstream, and Google Fiber (**Figure 1A** in the appendix displays their 2018 footprints).

6. Basic Entry Game

Suppose two firms, AT&T and Comcast $f \in \{a, c\}$ simultaneously decide whether to enter a market (CBG). The variable d_f denotes a provider's decision to enter, $d_f = 1$ if the firm chooses to enter and $d_f = 0$ otherwise. The set of firms' payoffs V_f is given by,

$$V_f = \begin{cases} \pi_{f0} = 0 & \text{if } d_f = 0 \\ \pi_{f1} = X\beta + \alpha_f - \gamma \cdot d_{-f} + \epsilon_{f1} & \text{if } d_f = 1 \end{cases}$$

where π_{f0} , the payoff from not entering, is normalized to zero, and π_{f1} , the payoff from entering depends upon, among other things, the entry decision of the firm's rival d_{-f} .

X includes both demand and supply factors that affect providers' payoffs, and β represents the payoff associated with these factors. For example, X might include a measure of market size (population or households), consumers' level of income, and other demographic information correlated with demand for broadband, as well as factors correlated with variable costs of network operation such as land area, housing units, and road miles. α_f is a firm-specific constant (fixed effect), and γ is the effect of competition on the firm's payoff when it faces a rival in the market. Note, I assume that β and γ are common to both firms. Finally, ϵ_{f1} represents the firm's private information about the profitability of entering the market (usually interpreted as the firm's private cost information). **Table 3** below summarizes the set of possible realized payoffs.

Table 3. Entry Game Realized Payoffs

(d_a, d_c)	V_a	V_c
(0, 0):	0	0
(1, 0):	$X\beta + \alpha_a + \epsilon_{a1}$	0
(0, 1):	0	$X\beta + \alpha_c + \epsilon_{c1}$
(1, 1):	$X\beta + \alpha_a - \gamma + \epsilon_{a1}$	$X\beta + \alpha_c - \gamma + \epsilon_{c1}$

6.1 Firms' Entry Decisions

Each firm makes a decision to enter the market based on its expected payoff, which depends on the probability that its rival enters p_{-f} . In my two firm example, AT&T and Comcast's expected payoffs are given by,

$$\mathbb{E}[\pi_{a1}] = X\beta + \alpha_a - \gamma \cdot p_{c1} + \epsilon_{a1}$$

$$\mathbb{E}[\pi_{c1}] = X\beta + \alpha_c - \gamma \cdot p_{a1} + \epsilon_{c1}$$

If AT&T believes Comcast plays a best-response (maximizes its profits) conditional on its private information, then the probability that Comcast enters is given by,

$$p_{c1}(d_c = 1|X; \beta, \gamma) = \mathcal{P}(\mathbb{E}[\bar{\pi}_{c1}] + \epsilon_{c1} \geq 0)$$

Assuming ϵ_{f1} is i.i.d. type 1 extreme value, from AT&T's perspective, Comcast's probability of entry can be written as the logit function,

$$p_{c1} = \frac{\exp(\mathbb{E}[\bar{\pi}_{c1}])}{1 + \exp(\mathbb{E}[\bar{\pi}_{c1}])}$$

Likewise, Comcast's beliefs about AT&T's service quality choice are given by,

$$p_{a1} = \frac{\exp(\mathbb{E}[\bar{\pi}_{a1}])}{1 + \exp(\mathbb{E}[\bar{\pi}_{a1}])}$$

6.2 Game Equilibria

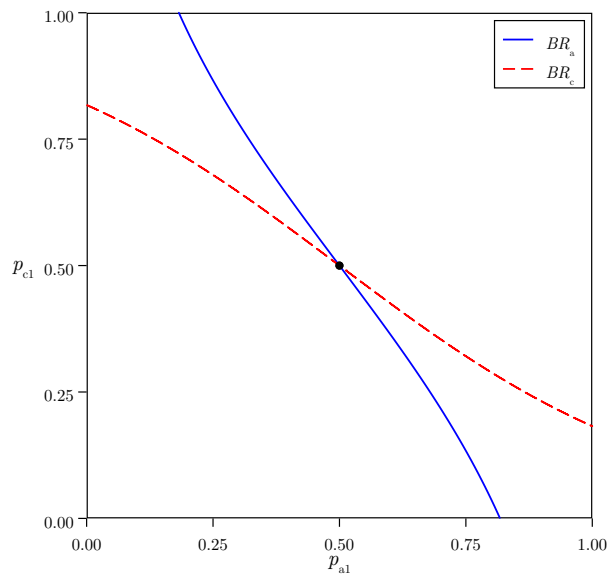
An equilibrium in this game is a Bayesian Nash equilibrium (BNE) which solves the system of equations $\mathbf{p}^* = \Psi(\mathbf{p}^*)$, where $\Psi(\cdot)$ represents the firms' best-response functions. Since I assume that ϵ_{f1} is i.i.d. type 1 extreme value, in this case a BNE satisfies the equations,

$$p_{a1}^* = \frac{\exp(X\beta + \alpha_a - \gamma \cdot p_{c1}^*)}{1 + \exp(X\beta + \alpha_a - \gamma \cdot p_{c1}^*)}$$

$$p_{c1}^* = \frac{\exp(X\beta + \alpha_c - \gamma \cdot p_{a1}^*)}{1 + \exp(X\beta + \alpha_c - \gamma \cdot p_{a1}^*)}$$

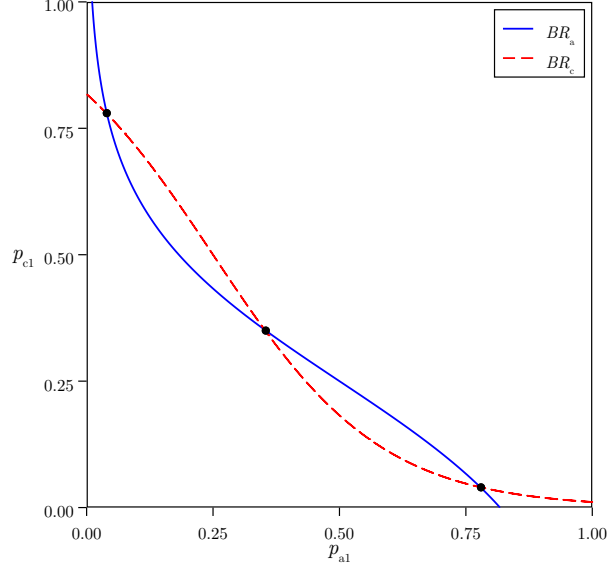
A standard identification problem in the estimation of games is that multiple equilibria may exist. For instance, for a particular set of parameter values $(\beta, \alpha_a, \alpha_c, \gamma)$ there may be more than one solution to the system of equations $\mathbf{p}^* = \Psi(\mathbf{p}^*)$, which means that the parameters do not necessarily uniquely identify the equilibrium that is represented by firms' choices in the data. Below I illustrate two cases, one where a unique equilibrium exists and one where multiple equilibria exist.

Figure 2. Unique Equilibrium
 $(\beta = 1, \alpha_a = 0.5, \alpha_c = 0.5, \gamma = -3)$



In **Figure 2**, I depict the case where a unique equilibrium exists. In this case, the payoff from entering

Figure 3. Multiple Equilibria
 $(\beta = 1, \alpha_a = 0.5, \alpha_c = 0.5, \gamma = -6)$



the market consists of $(\beta = 1)$ plus a firm specific constant (either $\alpha_a = 0.5$ or $\alpha_c = 0.5$), as well as a penalty ($\gamma = -3$) when a rival also chooses to enter the market. I plot both firms' best-response functions, which intersect only once at the equilibrium probabilities of entry ($p_{a1}^* = 0.50, p_{c1}^* = 0.50$). In this parameterization, the probabilities that AT&T and Comcast enter are completely identified by the set of parameters.

In **Figure 3**, I increase the effect of competition to $(\gamma = -6)$, holding constant the other parameters, and replot the firms' best-response functions. In this case, the firms' best-response functions intersect at three different points, and therefore, three possible equilibria exist: $\{(p_{a1}^* = 0.04, p_{c1}^* = 0.78), (p_{a1}^* = 0.35, p_{c1}^* = 0.35), (p_{a1}^* = 0.78, p_{c1}^* = 0.04)\}$. Even with data on firms' choices, we cannot identify which equilibrium was played in the game, however, the data may suggest that one equilibrium was more likely played than others. For example, if we observe that AT&T entered the market, while Comcast did not, then it is more likely that the equilibrium $(p_{a1}^* = 0.78, p_{c1}^* = 0.04)$ was actually played.

Using the idea that firms' observed choices can guide us towards identifying the equilibrium that was played in the data is the basis of estimation techniques that can deal with the possibility of multiple equilibria in determining the underlying parameters of the game. I discuss these in detail in the estimation section.

6.3 Likelihood Function

Setting aside for now whether or not multiple equilibria exist, given that the firms' probabilities of entry satisfy a BNE $\mathbf{p}^* = \Psi(\mathbf{p}^*)$, the likelihood contribution of market m can be expressed as the joint probability of all firms' observed entry decisions,

$$\ell_m = \prod_{f \in F} (p_{fm}^*)^{d_{fm}} \cdot (1 - p_{fm}^*)^{(1 - d_{fm})}$$

and the log-likelihood function is the sum of the log-likelihood contributions over all markets.

$$\log(\mathcal{L}) = \sum_{m=1}^M \sum_{f \in F} d_{fm} \cdot \log(p_{fm}^*) + (1 - d_{fm}) \cdot \log(1 - p_{fm}^*)$$

7. Full Entry and Quality Game with Fixed Costs

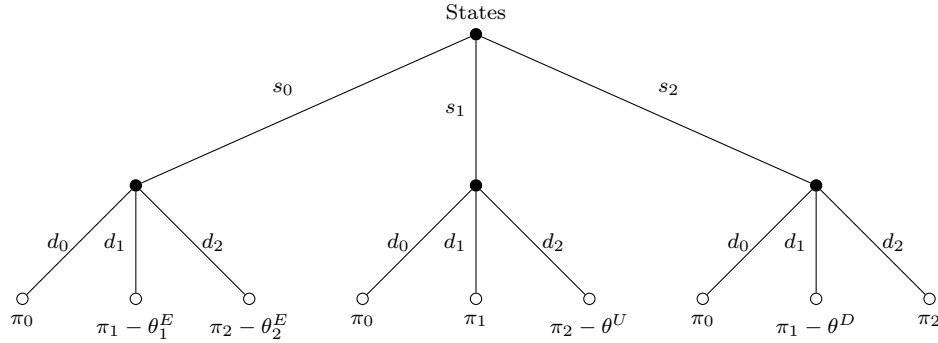
Building on the basic entry model described above, I incorporate both firms' quality choices and historical states, which allows me to identify providers' fixed costs of entry and upgrading/downgrading service. Specifically, suppose now that AT&T and Comcast simultaneously decide whether to operate in a market (CBG) as well as the quality of broadband to provide to consumers in that market. The variable d_{fq} denotes a firm's decision to operate and provide service of quality q . In this case, I assume $q \in \{1, 2\}$ and that the choice of quality within a CBG is mutually exclusive. The variable s_{fq} denotes the firm's state i.e. its decision to operate and provide service of quality q in the previous period. The set of firms' payoffs V_f is given by,

$$V_f = \begin{cases} \pi_{f0} = 0 & \text{if } d_{f1} = d_{f2} = 0 \\ \pi_{f1} = X\beta_1 + \alpha_{f1} - \gamma_{11} \cdot d_{-f1} - \gamma_{12} \cdot d_{-f2} - \theta_1^E \cdot (1 - s_{f1} - s_{f2}) - \theta^D \cdot s_{f2} + \epsilon_{f1} & \text{if } d_{f1} = 1 \\ \pi_{f2} = X\beta_2 + \alpha_{f2} - \gamma_{21} \cdot d_{-f1} - \gamma_{22} \cdot d_{-f2} - \theta_2^E \cdot (1 - s_{f1} - s_{f2}) - \theta^U \cdot s_{f1} + \epsilon_{f2} & \text{if } d_{f2} = 1 \end{cases}$$

where π_{f0} , the payoff from not operating, is normalized to zero, π_{f1} is the payoff from operating as a quality level 1 provider, and π_{f2} is the payoff from operating as a quality level 2 provider.

Again, X is a vector of market characteristics associated with the supply and demand for broadband. (β_1, β_2) are quality-specific vectors, $(\alpha_{f1}, \alpha_{f2})$ are firm-quality-specific fixed-effects, $(\gamma_{11}, \gamma_{12}, \gamma_{21}, \gamma_{22})$ are the effects of competition from rivals of different quality levels, $(\theta_1^E, \theta_2^E, \theta^D, \theta^U)$ are fixed costs of entering, downgrading service and upgrading service, and $(\epsilon_{f1}, \epsilon_{f2})$ is the firm's quality-specific private cost information. Slightly abusing notation, I depict the firm's payoffs depending upon its state and operation decision below in **Figure 4**.

Figure 4. Firm's Payoffs



7.1 Likelihood Function

As in the basic entry game, an equilibrium in this game is a Bayesian Nash equilibrium (BNE) which solves the system of equations $\mathbf{p}^* = \Psi(\mathbf{p}^*)$, where $\Psi(\cdot)$ represents the firms' best-response functions. In this case, given that the firms' probabilities of entry satisfy a BNE $\mathbf{p}^* = \Psi(\mathbf{p}^*)$, the likelihood contribution of market m can be expressed as the joint probability of all firms' observed operation decisions,

$$\ell_m = \prod_{f \in F} (p_{f1m}^*)^{d_{f1m}} \cdot (p_{f2m}^*)^{d_{f2m}} \cdot (1 - p_{f1m}^* - p_{f2m}^*)^{(1 - d_{f1m} - d_{f2m})}$$

and the log-likelihood function is the sum of the log-likelihood contributions over all markets.

$$\log(\mathcal{L}) = \sum_{m=1}^M \sum_{f \in F} d_{f1m} \cdot \log(p_{f1m}^*) + d_{f2m} \cdot \log(p_{f2m}^*) + (1 - d_{f1m} - d_{f2m}) \cdot \log(1 - p_{f1m}^* - p_{f2m}^*)$$

8. Estimation

Using data on ISPs' entry and quality choice decisions and market characteristics from 2017 and 2018, I estimate both the basic entry game and full entry and quality game. In the spirit of Seim (2006), Mazzeo (2002), and Augereau, Greenstein, and Rysman (2006) I assume that the static game I estimate approximates long-run market behavior. Below I describe the methods and data I use to estimate the models and discuss the results.

To estimate the parameters of each game I use the two-step and k-step Nested Pseudo Likelihood (NPL) methods of Aguirregabiria and Mira (2002, 2007), which are robust to the presence of multiple equilibria given that the system of players' best-response functions is stable. In this section I outline both procedures using the basic entry game as an example, but I also use these methods to estimate the full entry and quality game. In general, estimation of the parameters of a static game of incomplete information via maximum likelihood can be represented as a constrained optimization problem in which the objective is to search for a vector of parameters θ that maximizes the log-likelihood function subject to the constraint that the players' strategies $\mathbf{p}_m(\theta) = \{p_{1m}, \dots, p_{Fm}\}$ satisfy a BNE in each market,

$$\begin{aligned} & \max_{\{\theta\}} \log(\mathcal{L}(\theta)) \\ & \text{s.t. } \mathbf{p}_m^*(\theta) = \Psi(\mathbf{p}_m^*(\theta)), \forall m = 1, \dots, M \end{aligned}$$

Searching for solutions to this problem is computationally burdensome and complicated by the possibility of multiple equilibria (described previously). Aguirregabiria and Mira (2002, 2007) show that NPL can be used to consistently estimate static and dynamic games.

8.1 Two-step NPL

In two-step NPL (2-NPL), I define a pseudo likelihood function where players' choice probabilities are best responses to an arbitrary \mathbf{p} ; "pseudo" because \mathbf{p} does not represent equilibrium probabilities but can be

interpreted as players' beliefs about the actions of other players. For the basic entry game the pseudo likelihood function is,

$$\log(\mathcal{L}) = \sum_{m=1}^M \sum_{f \in F} d_{fm} \cdot \log(p_{fm}^{(1)}) + (1 - d_{fm}) \cdot \log(1 - p_{fm}^{(1)})$$

Step 1. In the first step of the procedure, I estimate an initial vector of firms' beliefs without considering strategic behavior. If \mathbf{p}^0 is the true vector of conditional choice probabilities, we can consistently estimate each element of \mathbf{p}^0 nonparametrically using a simple frequency estimator,

$$\hat{p}_{fim}^{(0)} = \frac{\sum_{m=1}^M d_{fim} \cdot \mathbb{1}\{X_m = X^b\}}{\sum_{m=1}^M \mathbb{1}\{X_m = X^b\}}$$

where $\mathbb{1}\{X_m = X^b\}$ is an indicator function that denotes whether the vector of market characteristics in market m falls within a certain bin.

Step 2. In the second step, I plug the first-step estimates of firms' choice probabilities into firms' best-response functions and estimate a standard multinomial logit. In the basic entry game with two firms for example,

$$p_{a1m}^{(1)} = \frac{\exp(X_m \beta + \alpha_a - \gamma \cdot \hat{p}_{c1m}^{(0)})}{1 + \exp(X_m \beta + \alpha_a - \gamma \cdot \hat{p}_{c1m}^{(0)})}$$

$$p_{c1m}^{(1)} = \frac{\exp(X_m \beta + \alpha_c - \gamma \cdot \hat{p}_{a1m}^{(0)})}{1 + \exp(X_m \beta + \alpha_c - \gamma \cdot \hat{p}_{a1m}^{(0)})}$$

Relying on the first-step estimates of firms' beliefs, this procedure resolves the multiple equilibria problem by selecting the equilibrium that was played in the data.

8.2 K-step NPL

Because two-step procedure suffers from small sample bias when the first-step estimates of players' CCPs are not consistent, Aguirregabiria and Mira (2002, 2007) proposed the k-step NPL estimator (k-NPL), which is consistent regardless of whether or not the first-step estimates are consistent. The k-NPL estimator is an iterative version of the two-step estimator in which player' best-response functions continue to be updated based upon previous estimates of θ until a fixed-point is found in each market. For example, in the basic entry game we could continue to update firms' best-responses based on parameter estimates $\theta^{(k)}$,

$$p_{a1m}^{(k)} = \frac{\exp(X_m \beta^{(k)} + \alpha_a^{(k)} - \gamma^{(k)} \cdot p_{c1m}^{(k-1)})}{1 + \exp(X_m \beta^{(k)} + \alpha_a^{(k)} - \gamma^{(k)} \cdot p_{c1m}^{(k-1)})}$$

$$p_{c1m}^{(k)} = \frac{\exp(X_m \beta^{(k)} + \alpha_c^{(k)} - \gamma^{(k)} \cdot p_{a1m}^{(k-1)})}{1 + \exp(X_m \beta^{(k)} + \alpha_c^{(k)} - \gamma^{(k)} \cdot p_{a1m}^{(k-1)})}$$

iterating until $\|\mathbf{p}^{(k)} - \mathbf{p}^{(k-1)}\| < \epsilon$.

8.3 ISP Decisions and States

As discussed in the data section, I group service into two levels of quality based on transmission technology. For telco providers, broadband delivered over copper wire or DSL is level 1 quality service ($q = 1$), while broadband delivered via FTTP is considered level 2 quality service ($q = 2$). For cable providers, broadband delivered over DOCSIS 1, 1.1, 2.0, or 3.0 or another cable modem is level 1 quality service ($q = 1$), while broadband delivered via DOCSIS 3.1 is considered level 2 quality service ($q = 2$). **Table 4**, summarizes ISPs' entry and quality decision and states in 2017 and 2018.

Table 4. ISP Entry and Quality Decisions and States

2018						
Provider	Decisions			States		
	d_0	d_1	d_2	s_0	s_1	s_2
AT&T	151	447	2,089	129	720	1,838
Charter	2,012	0	675	2,014	673	0
Comcast	294	83	2,310	303	630	1,754
Google Fiber	2,532	0	155	2,574	0	113
Windstream	2,454	131	102	2,500	102	85
2017						
Provider	Decisions			States		
	d_0	d_1	d_2	s_0	s_1	s_2
AT&T	129	720	1,838	84	1,206	1,397
Charter	2,014	673	0	2,053	634	0
Comcast	303	630	1,754	330	2,357	0
Google Fiber	2,574	0	113	2,627	0	60
Windstream	2,500	102	85	2,372	233	82

8.4 Market Characteristics

Besides competition the main determinants of providers' entry and quality decisions in the model are market characteristics, specifically factors that affect supply and demand for broadband. Here I describe the major characteristics I consider for inclusion in my model, which are presented in **Table 5**. The most important demand-side factor in the literature is market size. Other papers in the empirical entry literature have generally used either population or number of businesses to measure market size. I collect census block group level demographic data from the ACS including population and number of households, as potential measures of market size. Importantly, I also utilize GIS data on block group area, which allows me to both capture the effect of market size density and control for the geographic size of each block group.

Other demographic factors likely correlated with demand for broadband include income, employment status, education, and age. Survey evidence from the FCC (2015) indicates that digital literacy may be especially important in explaining households' decisions to adopt broadband, therefore, I anticipate educational attainment to be positively correlated with demand and age to be negatively correlated with demand for broadband. On the supply-side, I collect data on several market characteristics likely to be correlated with ISPs' variable costs. To the extent that the number of housing units within a block group varies distinctly from population or number of households, holding market size constant, an increase in housing units should be associated with an increase in physical connections per unit of demand – in other words increased oper-

Table 5. Summary of Market Characteristics (2018)

	N	Mean	St. Dev.	Minimum	Median	Maximum
Population	2,687	2,224	1,347	0	1,946	12,037
Number of Households	2,687	792	451	0	710	4,001
Number of Housing Units	2,687	872	482	0	780	4,073
Per Capita Income	2,683	34,189	19,731	3,286	28,815	189,656
Median Household Income	2,632	71,405	37,611	2,499	63,386	250,001
% Bachelor's Degree or Higher	2,683	37	23	0	31	100
Median Age	2,683	38	8	11	37	81
Unemployment Rate	2,680	6	6	0	5	65
Land Area (miles ²)	2,687	3	8	0	1	134

Source: ACS 5-year estimates

ating costs or deployment costs. Additionally, variation in other types of variable costs such as right-of-way access across census block groups may be captured by geographic variation in property value or rent. For instance, Bresnahan and Reiss (1991) use data on farmland value as a proxy for cost.

8.5 Model Specifications

To simplify the estimation (in particular finding BNE solutions in each market), I include only the five largest ISPs: AT&T, Comcast, Charter, Windstream, and Google Fiber as players in each game. For baseline results, I specify relatively parsimonious payoff functions which depend on three market characteristics: market population, per capita income, and land area. Rather than combining population and land area into a measure of population density, I include these variables separately for a more flexible specification of firms' payoff functions.

In the basic entry game, each firm's $f \in F$ payoff from entering market $m = 1, \dots, M$ is given by,

$$\pi_{f1m} = X_m \beta + \alpha_f - \gamma \cdot \sum_{r \neq f}^F d_{r1m} + \epsilon_{f1m}$$

In the full entry and quality game, each firm's $f \in F$ payoffs from operating in market $m = 1, \dots, M$ as a level $q \in \{1, 2\}$ quality provider are given by,

$$\begin{aligned} \pi_{f1m} &= X_m \beta_1 + \alpha_{f1} - \gamma_{11} \cdot \sum_{r \neq f}^F d_{r1m} - \gamma_{12} \cdot \sum_{r \neq f}^F d_{r2m} - \theta_1^E \cdot (1 - s_{f1m} - s_{f2m}) - \theta^D \cdot s_{f2m} \\ &\quad - \theta_1^n \cdot (1 - s_{f1m} - s_{f2m}) \cdot \mathbb{1}\{n_{fm}\} + \epsilon_{f1m} \\ \pi_{f2m} &= X_m \beta_2 + \alpha_{f2} - \gamma_{21} \cdot \sum_{r \neq f}^F d_{r1m} - \gamma_{22} \cdot \sum_{r \neq f}^F d_{r2m} - \theta_2^E \cdot (1 - s_{f1m} - s_{f2m}) - \theta^U \cdot s_{f1m} \\ &\quad - \theta_2^n \cdot (1 - s_{f1m} - s_{f2m}) \cdot \mathbb{1}\{n_{fm}\} + \epsilon_{f2m} \end{aligned}$$

where the parameters θ_1^n, θ_2^n capture cost synergies from entering neighbouring markets.

8.6 Results

The estimation results are presented in **Tables 6–8**. The dependent variable in the basic model is the vector of firms’ joint entry decisions, while the dependent variable in the full model is the vector of providers’ joint operation and quality decisions. Both sets of estimates include the same market characteristics, as well as provider fixed-effects to capture observable firm heterogeneity.

Table 6 displays the parameter estimates of the basic entry game using 2018 data. Both the 2-NPL and k-NPL estimators produce parameter values of a similar pattern and of the expected sign. Generally, the results indicate that providers are more likely to serve more populated, denser, and wealthier markets, all else equal, and that competition has a negative effect on a firm’s probability of entry. Close comparison of the provider fixed-effects reveals that the relative order of the fixed-effects is consistent across estimators i.e. AT&T is most likely to enter followed by Comcast, and so on. Moreover, meaningful variation in the fixed-effects suggests that provider heterogeneity is important in explaining entry patterns across geographic markets. Although the 2-NPL and k-NPL estimates follow a similar pattern, the magnitude of the parameter values and standard errors are quite different. In particular, the 2-NPL estimate of the competition parameter γ is relatively large, while the k-NPL estimate is close to zero. Similarly the k-NPL market characteristic coefficients are attenuated. This pattern indicates that the game may not be stable in which case the k-NPL estimates are not consistent (Aguirregabiria 2019). If the game is indeed unstable, then the 2-NPL estimates are more likely to be representative of the “true” parameter values. However, because of this concern, when I estimate the full entry and quality game I check the stability of the game by calculating the spectral radius of the system of firms’ best-responses for each market using the 2-NPL estimates, as suggested by Aguirregabiria (2019). The 2-NPL and k-NPL estimates are much more similar for the full game, and calculation of the spectral radius indicates that the full game is stable (see appendix **Table 2B**).

Table 6. Basic Entry Game (2018)

	2-NPL	SEs	k-NPL	SEs
Population (000)	0.415	(0.018)	0.185	(0.072)
Per Capita Income (0,000)	0.204	(0.013)	0.059	(0.025)
Land Area (miles ²)	-0.063	(0.003)	-0.022	(0.008)
AT&T	9.275	(0.160)	2.448	(1.236)
Comcast	8.663	(0.154)	1.621	(1.307)
Charter	7.660	(0.173)	-1.587	(2.031)
Google Fiber	6.423	(0.186)	-3.452	(2.270)
Windstream	6.574	(0.181)	-2.970	(2.235)
γ	5.305	(0.090)	0.031	(1.138)
Log-Likelihood	-5852.454		-8431.875	
Markets	2,687		2,687	

Note (a): Observed information matrix standard errors in parentheses.

Table 7 displays estimates of the full game using 2018 data and **Table 8** displays estimates of the full game using pooled 2017 and 2018 data (2017-only estimates can be found in appendix **Table 3B**).

Table 7. Full Entry and Quality Game w/ Fixed Costs (2018)

	2-NPL	SEs	BS-SEs	5th, 95th Pct.	k-NPL	SEs
Quality Level: (q = 1)						
β_1 : Population (000)	0.223	(0.063)	[0.062]	[0.103, 0.313]	0.238	(0.065)
β_1 : Per Capita Income (0,000)	0.233	(0.037)	[0.036]	[0.161, 0.281]	0.245	(0.038)
β_1 : Land Area (miles ²)	-0.043	(0.009)	[0.010]	[-0.058, -0.024]	-0.045	(0.010)
α_1 : AT&T	3.856	(0.444)	[0.402]	[2.473, 3.802]	3.795	(0.447)
α_1 : Comcast	3.146	(0.493)	[0.478]	[1.558, 3.096]	3.053	(0.500)
α_1 : Windstream	4.089	(0.559)	[0.481]	[2.461, 4.029]	3.959	(0.566)
γ_{11}	0.329	(0.282)	[0.322]	[-0.089, 0.977]	-0.124	(0.325)
γ_{12}	0.171	(0.199)	[0.210]	[-0.143, 0.548]	0.209	(0.217)
Quality Level: (q = 2)						
β_2 : Population (000)	0.255	(0.059)	[0.062]	[0.143, 0.334]	0.277	(0.061)
β_2 : Per Capita Income (0,000)	0.283	(0.034)	[0.031]	[0.228, 0.332]	0.301	(0.034)
β_2 : Land Area (miles ²)	-0.084	(0.009)	[0.011]	[-0.105, -0.070]	-0.087	(0.010)
α_2 : AT&T	5.242	(0.380)	[0.369]	[5.420, 6.653]	5.212	(0.387)
α_2 : Comcast	6.953	(0.479)	[0.560]	[6.793, 8.627]	6.882	(0.489)
α_2 : Charter	6.037	(0.531)	[0.414]	[5.556, 6.837]	5.961	(0.544)
α_2 : Google Fiber	6.834	(0.539)	[0.580]	[6.363, 8.282]	6.748	(0.549)
α_2 : Windstream	4.860	(0.536)	[0.510]	[4.656, 6.367]	4.824	(0.547)
γ_{21}	1.188	(0.250)	[0.249]	[0.912, 1.701]	0.961	(0.291)
γ_{22}	1.326	(0.181)	[0.189]	[1.071, 1.685]	1.412	(0.200)
Fixed Costs						
θ_1^E	9.111	(0.468)	[0.373]	[7.593, 8.831]	9.055	(0.468)
θ_2^E	10.383	(0.392)	[0.438]	[9.959, 11.385]	10.286	(0.392)
θ^D	4.718	(0.416)	[0.386]	[2.664, 3.969]	4.736	(0.418)
θ^U	0.477	(0.354)	[0.299]	[1.503, 2.461]	0.457	(0.355)
θ_1^n	-0.877	(0.350)	[0.319]	[-1.310, -0.281]	-0.855	(0.352)
θ_2^n	-1.869	(0.252)	[0.267]	[-2.227, -1.370]	-1.884	(0.252)
Log-Likelihood	-1660.037				-1658.602	
Markets	2,687				2,687	

Note (a): Observed information matrix standard errors in parentheses.

Note (b): Bootstrapped standard errors and confidence intervals in brackets (250 repetitions).

Table 8. Full Entry and Quality Game w/ Fixed Costs (Pooled)

	2-NPL	SEs	k-NPL	SEs
Quality Level: (q = 1)				
β_1 : Population (000)	0.050	(0.038)	0.050	(0.039)
β_1 : Per Capita Income (0,000)	0.158	(0.026)	0.160	(0.027)
β_1 : Land Area (miles ²)	-0.032	(0.005)	-0.032	(0.005)
α_1 : AT&T	3.968	(0.211)	3.796	(0.217)
α_1 : Comcast	4.316	(0.239)	4.154	(0.249)
α_1 : Charter	3.910	(0.241)	3.729	(0.252)
α_1 : Windstream	2.465	(0.247)	2.264	(0.262)
γ_{11}	0.816	(0.120)	0.663	(0.142)
γ_{12}	0.961	(0.113)	0.904	(0.129)
Quality Level: (q = 2)				
β_2 : Population (000)	0.162	(0.037)	0.130	(0.038)
β_2 : Per Capita Income (0,000)	0.226	(0.025)	0.211	(0.026)
β_2 : Land Area (miles ²)	-0.050	(0.005)	-0.046	(0.005)
α_2 : AT&T	5.512	(0.245)	5.391	(0.248)
α_2 : Comcast	7.413	(0.292)	7.325	(0.297)
α_2 : Charter	5.911	(0.301)	5.729	(0.308)
α_2 : Google Fiber	7.210	(0.340)	7.007	(0.346)
α_2 : Windstream	2.979	(0.285)	2.820	(0.293)
γ_{21}	1.223	(0.122)	1.361	(0.145)
γ_{22}	1.061	(0.113)	0.852	(0.128)
Fixed Costs				
θ_1^E	7.161	(0.182)	7.135	(0.184)
θ_2^E	10.503	(0.274)	10.473	(0.274)
θ^D	2.787	(0.241)	2.768	(0.241)
θ^U	2.045	(0.189)	2.022	(0.189)
θ_1^n	-1.423	(0.200)	-1.433	(0.200)
θ_2^n	-1.762	(0.177)	-1.757	(0.176)
Log-Likelihood	-6,153.136		-6,141.917	
Markets	2,687		2,687	
Years	2		2	
Observations	5,374		5,374	

Note (a): Observed information matrix standard errors in parentheses.

Estimates of the competition parameters ($\gamma_{11}, \gamma_{12}, \gamma_{21}, \gamma_{22}$) are generally of the expected sign, although they vary depending on the specification. In particular, the effects of competition on low quality providers are close to zero and statistically insignificant in the 2018 specification, likely due to the limited number of observations for low quality service in 2018. Given the importance of correctly identifying the effects of competition in my application, I concentrate on the pooled estimates in this discussion and rely on them for purposes of my counterfactual simulations.

Consistent with the results of the basic entry game, estimates of the full game across all specifications indicate that providers are more likely to operate in more populated, denser, and wealthier markets. Additionally, the results show that ISPs are more likely to offer high quality service in more populated, denser, and wealthier markets indicated by the larger coefficients on population and income and smaller coefficient on land area for high quality providers. This result is consonant with the underlying economic forces that govern the broadband market; providers have an incentive to vertically differentiate or bear the cost of building out more expensive high speed networks (or upgrade their existing networks) in larger and denser markets due to economies of scale and density.

With respect to competition, the pooled estimates of the competitive effects are of the expected signs and statistically significant. $\gamma_{12} > \gamma_{11}$ indicating that competition from high quality providers has a greater impact on the profits of low quality firms than competition from low quality providers, which is expected. However, $\gamma_{21} > \gamma_{22}$ indicating opposite is true for high quality providers' payoffs, which is less intuitive. We might expect firms to differentiate within markets in order to soften competition, however, the pattern of competitive effects from the model suggests that differentiating is not the more profitable strategy. This is the opposite of the pattern Mazzeo (2002) finds in his study of the motel industry, where in general differentiation appears to be the more profitable strategy. Because there is good reason to believe differentiation should soften competition, we might be skeptical that competitive effects are correctly identified. A likely cause is omission of relevant market characteristics, either supply or demand-side factors, that are correlated with firms' decisions. One solution would be to include additional market characteristics in the model, another would be to account for unobservable heterogeneity across markets by specifying a random effect. Aguirregabiria and Mira (2007) and Arcidiacono and Miller (2011) show that not accounting for unobserved market heterogeneity can bias estimates of competition parameters and develop methods to estimate games with unobserved heterogeneity. Further analysis should be done to investigate whether the pattern of competitive effects I obtain with the baseline model is reasonable.

Finally, the fixed cost parameters are of the expected sign, relatively large, and quite intuitive. Specifically, the costs of entry for both types of providers (θ_1^E, θ_2^E) are of a similar magnitude, but the cost of entry for high quality providers is greater, as expected. The cost of upgrading service from low to high quality θ^U is less than the cost of downgrading service θ^D , which seems to reflect the sunk cost of building out high quality service. Also, the estimates of (θ_1^n, θ_2^n) indicate that the cost of entering neighbouring markets is less than the cost of entering non-neighbouring markets, which is plausible given we would expect to observe cost synergies in network deployment. Taken altogether, the model appears to capture the core economic factors affecting ISPs' entry and quality decisions reasonably well, and the model fits the data well (see appendix **Table 1B**).

8.7 Competitive Effects and Fixed Costs

In order to get a sense of the magnitude of the competitive effects (as well as fixed cost parameters), I calculate the ratio of the parameters to the monopoly profits implied by the pooled model estimates (Lin (2015) undertakes a similar exercise for the nursing home industry). Defining the mean implied monopoly profits for each quality level as,

$$E[\pi_{f1}^m] = \frac{1}{M} \sum_{m=1}^M (X\hat{\beta}_1 + \hat{\alpha}_{f1})$$

$$E[\pi_{f2}^m] = \frac{1}{M} \sum_{m=1}^M (X\hat{\beta}_2 + \hat{\alpha}_{f2})$$

I compute the ratio of each competition and fixed cost parameter to estimated monopoly profits, e.g. $\frac{\gamma_{11}}{E[\pi_{1f}^m]}$, in **Table 9**. The ratio of the competitive effects $(\gamma_{11}, \gamma_{12}, \gamma_{21}, \gamma_{22})$ to mean monopoly profits approximates the percent reduction in profit due to facing a competitor of a particular quality in the average market. For example, competition from a low quality competitor reduces AT&T's profits by approximately 15% when it offers low quality service and 22% when it offers high quality service. Competition from a high quality provider reduces AT&T's profits by approximately 21% when it offers low quality service and 13% when it offers high quality service. The ratio of fixed costs to monopoly profits show that entry costs are roughly 1.6 times the size of AT&T's monopoly profits regardless of quality choice. The ratio of parameters to monopoly profits are similar across providers with the exception of Windstream, which has smaller fixed effects and thus the ratio of parameters to monopoly profits is larger. Variation in implied monopoly profits across firms (the fixed-effects) can be interpreted in several ways. α_{fq} can represent either supply-side or demand-side factors that affect profits, so a relatively high α_{fq} may indicate that a provider has a cost advantage or that consumers prefer its services, all else equal.

**Table 9. Ratio of Parameters to Mean Monopoly Profits
(Pooled Estimates)**

Parameter/Profit	AT&T	Comcast	Charter	Google	Windstream
$E[\pi_1^m]$	4.330	4.688	4.263	N/A	2.798
γ_{11}	0.153	0.141	0.156	N/A	0.237
γ_{12}	0.209	0.193	0.212	N/A	0.323
θ_1^E	1.648	1.522	1.674	N/A	2.550
θ^U	0.467	0.431	0.474	N/A	0.723
θ_1^n	0.331	0.306	0.336	N/A	0.512
$E[\pi_2^m]$	6.226	8.160	6.564	7.842	3.655
γ_{21}	0.219	0.167	0.207	0.174	0.372
γ_{22}	0.137	0.104	0.130	0.109	0.233
θ_2^E	1.682	1.283	1.595	1.335	2.865
θ^D	0.445	0.339	0.422	0.353	0.757
θ_2^n	0.282	0.215	0.268	0.224	0.481

9. Counterfactual Analysis

The question at the heart of this paper is how does competition effect ISPs' quality choices? The estimates of the structural model alone are not sufficient to answer this question, because firms' choices are the result of equilibrium behavior. Thus, in order to determine the extent to which competition effects ISPs' decisions to improve quality I conduct two counterfactual experiments using the pooled model estimates. In the first, I simulate firms' choices absent the effect of competition – essentially I compare providers' predicted entry and quality choices under imperfect competition to what firms would have chosen if they behaved as monopolists. In the second counterfactual, I simulate increases in competitive pressure through a reductions in entry costs for high quality service – in effect a subsidy to providers willing to deploy high quality service. Both of these counterfactuals shed light on the relationship between competition and quality, albeit through different channels. The first counterfactual represents a direct effect of a change in the degree of competition, while the second, represents an indirect effect of a change in the degree of competition through a change in fixed costs. As a preview, I find that if providers behaved as monopolists they would have a greater incentive to offer high quality service and that large reductions in entry costs are necessary to incentivize providers to deploy high quality service. Thus, at least within the constraints of my analysis, I find that competition does not appear to incentivize firms to offer high quality service in the broadband market. First, I describe the general method I use to perform both counterfactual experiments, then I discuss the specification and results of each in detail.

9.1 Counterfactual Method

In order to implement each counterfactual experiment, I use the method of iteration. More explicitly, I perturb the parameters of interest $\theta \rightarrow \hat{\theta}$, then iterate on firms' best-responses to find choice probabilities that satisfy a BNE $\mathbf{p}^* = \Psi(\mathbf{p}^*(\hat{\theta}))$ in each market $m = 1, \dots, M$. I start from the choice probabilities predicted by the pooled model estimates and update firms' best-responses until $\|\mathbf{p}^{(k)} - \mathbf{p}^{(k-1)}\| < \epsilon$ in each market. The advantage of this method is its simplicity, the downside is that it ignores the possibility of multiple equilibria. However, in the case of the first counterfactual this is a non-issue since removing the effects of competition also eliminates the possibility of multiple equilibria. In the case of the second counterfactual, I verify that the predictions of the model don't jump around as I perturb the fixed cost parameter, and the results show that reductions in fixed cost have a gradual and consistent effect on predicted outcomes.

For each counterfactual analysis, I report firms' mean predicted choice probabilities and predicted decisions based on these probabilities for the year 2018. More precisely, if the vector $(\hat{p}_{f0m}, \hat{p}_{f1m}, \hat{p}_{f2m})$ is the set of firm f 's predicted choice probabilities for market m , then the predicted decision of firm f for market m is given by the maximum choice probability,

$$\hat{d}_{fq} = \begin{cases} 1 & \text{if } \hat{p}_{fq} = \max \{(\hat{p}_{f0}, \hat{p}_{f1}, \hat{p}_{f2})\} \\ 0 & \text{otherwise} \end{cases}$$

9.2 Counterfactual (1): No Competition

As discussed above, in the first counterfactual I set the competition parameters equal to zero, $(\gamma_{11}, \gamma_{12}, \gamma_{21}, \gamma_{22}) = (0, 0, 0, 0)$. This experiment essentially asks the question, if each firm operated as a monopolist how would its incentives to enter/operate as a low or high quality provider change? This exercise gets at a key issue in oligopoly theory as to whether or not competition spurs firms to improve product quality. The results reported in **Tables 10 and 11** below show that in this case competition appears to negatively affect the incentive to offer high quality service (displayed graphically in appendix **Figure 2A**). Comparing the choice probabilities predicted by the model to the counterfactual choice probabilities, on average each firm is more likely to operate as a high quality provider when it faces no competition. However, because the structural model allows firms to have heterogeneous payoffs, the effect size varies substantially across providers. The change in the firms' choice probabilities range from 0.5% in the case of Windstream to 9% in the case of Google Fiber. The predicted decisions show a similar pattern.

**Table 10. Counterfactual (1): No Competition ($\gamma = 0$)
Mean Choice Probabilities (2018)**

Provider	Predicted			Counterfactual		
	p_0	p_1	p_2	p_0	p_1	p_2
AT&T	0.0579	0.1597	0.7824	0.0450	0.1575	0.7975
Charter	0.7415	0.1233	0.1352	0.6686	0.1655	0.1659
Comcast	0.1040	0.0573	0.8387	0.0745	0.0618	0.8638
Google Fiber	0.9374	0.0000	0.0626	0.8465	0.0000	0.1535
Windstream	0.9407	0.0270	0.0323	0.9159	0.0453	0.0388

**Table 11. Counterfactual (1): No Competition ($\gamma = 0$)
Decisions (2018)**

Provider	Actual			Predicted			Counterfactual		
	d_0	d_1	d_2	d_0	d_1	d_2	d_0	d_1	d_2
AT&T	151	447	2,089	129	673	1,885	129	684	1,874
Charter	2,012	0	675	2,014	212	461	2,013	49	625
Comcast	294	83	2,310	303	2	2,382	296	0	2,391
Google Fiber	2,532	0	155	2,574	0	113	2,531	0	156
Windstream	2,454	131	102	2,509	96	82	2,501	101	85

9.3 Counterfactual (2): Fixed Cost Reduction

In the second counterfactual, I multiply the fixed entry cost parameter for high quality service θ_2^E by a factor $(1 - r)$, where r is the percent reduction in the cost of entry. I choose several values of $r = \{0.1, 0.2, 0.3, 0.4\}$ in order to assess the effects of a range of potential subsidies. To get a sense of the magnitude of these reductions in terms of provider profits, I multiply the ratio of θ_2^E to $E[\pi_{1f}^m]$ in **Table 9** by r for AT&T, which implies that the percent reductions in the entry cost correspond to subsidies that are approximately 16.8%, 33.6%, 50.5%, and 67.3% of monopoly profits, respectively. The results of these reductions in the cost of entry reported in **Tables 12 and 13** show that subsidies to high quality service increase providers' incentives to deploy high quality service, as expected, however, like the previous counterfactual firms are heterogeneous the effect size varies substantially across providers (displayed graphically in appendix **Figure 3A**). Also because providers' choices are determined in equilibrium in this counterfactual, we see that providers with larger fixed effects, reflecting revenue or cost advantages, are even more likely to offer high quality service on average (not only because they have a profit advantage but because their competitors know that they have an advantage). The change in firms' choice probabilities range from 0.7% in the case of Windstream to 38% in the case of Google Fiber, and again, firms' predicted decisions show a similar pattern. Finally, I note that the marginal increase in the probability that a provider offers high quality service with respect to a fixed cost reduction appears to be smooth.

Table 12. Counterfactual (2): Fixed Cost Reduction (θ_2^E)
Mean Choice Probabilities (2018)

Provider	Predicted			10% Reduction			20% Reduction		
	p_0	p_1	p_2	p_0	p_1	p_2	p_0	p_1	p_2
AT&T	0.0579	0.1597	0.7824	0.0576	0.1593	0.7831	0.0570	0.1584	0.7846
Charter	0.7415	0.1233	0.1352	0.7343	0.1222	0.1434	0.7170	0.1202	0.1628
Comcast	0.1040	0.0573	0.8387	0.0965	0.0566	0.8470	0.0821	0.0552	0.8627
Google Fiber	0.9374	0.0000	0.0626	0.9057	0.0000	0.0943	0.8393	0.0000	0.1607
Windstream	0.9407	0.0270	0.0323	0.9406	0.0268	0.0327	0.9402	0.0263	0.0335
Provider	30% Reduction			40% Reduction					
	p_0	p_1	p_2	p_0	p_1	p_2			
AT&T	0.0557	0.1567	0.7876	0.0536	0.1541	0.7924			
Charter	0.6803	0.1171	0.2026	0.6139	0.1132	0.2729			
Comcast	0.0624	0.0534	0.8842	0.0433	0.0515	0.9052			
Google Fiber	0.7225	0.0000	0.2775	0.5546	0.0000	0.4454			
Windstream	0.9393	0.0253	0.0354	0.9369	0.0237	0.0393			

**Table 13. Counterfactual (2): Fixed Cost Reduction (θ_2^F)
Decisions (2018)**

Provider	Actual			Predicted			10% Reduction		
	d_0	d_1	d_2	d_0	d_1	d_2	d_0	d_1	d_2
AT&T	151	447	2,089	129	673	1,885	129	669	1,889
Charter	2,012	0	675	2,014	212	461	2,014	211	462
Comcast	294	83	2,310	303	2	2,382	303	2	2,382
Google Fiber	2,532	0	155	2,574	0	113	2,569	0	118
Windstream	2,454	131	102	2,509	96	82	2,509	96	82
Provider	20% Reduction			30% Reduction			40% Reduction		
	d_0	d_1	d_2	d_0	d_1	d_2	d_0	d_1	d_2
AT&T	129	665	1,893	129	659	1,899	126	650	1,911
Charter	2,013	209	465	2,006	207	474	1,884	199	604
Comcast	292	2	2,393	127	2	2,558	83	2	2,602
Google Fiber	2,496	0	191	2,247	0	440	1,909	0	778
Windstream	2,510	95	82	2,510	95	82	2,511	94	82

10. Conclusion

This paper contributes to the empirical literature analyzing the relationship between market structure and product quality in the telecommunications industry. Using geographic data on ISPs coverage area I examine the extent to which competition affects quality in the market for broadband. My results suggest that ISPs would have increased incentive to deploy high quality broadband if they behaved as monopolists, and that though reductions in the cost of entry for high quality service would increase firms' incentives to offer faster service, the magnitude of these subsidies would have to be quite large in order to incentivize meaningful changes in quality. These results depend in part upon the estimates of the competition parameters in my model, thus it is important to several potential sources of bias that could impact the estimates I obtain. First, as Aguirregabiria and Mira (2007) and Arcidiacono and Miller (2011) point out, omission of unobserved market heterogeneity may result in misleading estimates of competition parameters. Second, omission of the effect of potential entry (from players outside observed markets) may also bias these estimates. For example, Seim (2006) addresses this source of bias by making arbitrary assumptions about number of potential entrants, while Fan and Xiao (2015) model potential entry using industry-wide data. Third, due to the complexity of the model, my specification of firms' payoff functions is relatively restrictive. Determining the sensitivity of my estimates to unobserved heterogeneity, potential entry, and functional form will be a focus of continued work on this topic.

It is also important to emphasize the main limitation of my methodology – without product-level data on providers' prices and quantities, I am not able to make inferences about changes in consumer surplus as a result of changes in market structure. While my estimates indicate firms have more incentive to improve quality as monopolists, it's very possible, and even likely, that consumer surplus would be greater under imperfect competition than monopoly, though providers' incentives to improve quality would be weaker. For example, Goettler and Gordon (2011) show that although an Intel monopoly in the hard drive industry would have resulted in a faster rate of innovation, consumer surplus was greater under an AMD-Intel duopoly. This is because the gain in consumer surplus as a result of higher quality under an Intel monopoly would not have

been great enough to offset the decrease as a result of monopoly pricing. Therefore, while this paper may be useful for thinking about how competition-related policy might affect ISPs' deployment choices, we should be cautious about drawing inferences regarding the relationship between market structure and consumer welfare.

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Appendices

A. Additional Figures

Figure 1A. Major ISP Coverage Areas by Quality Level

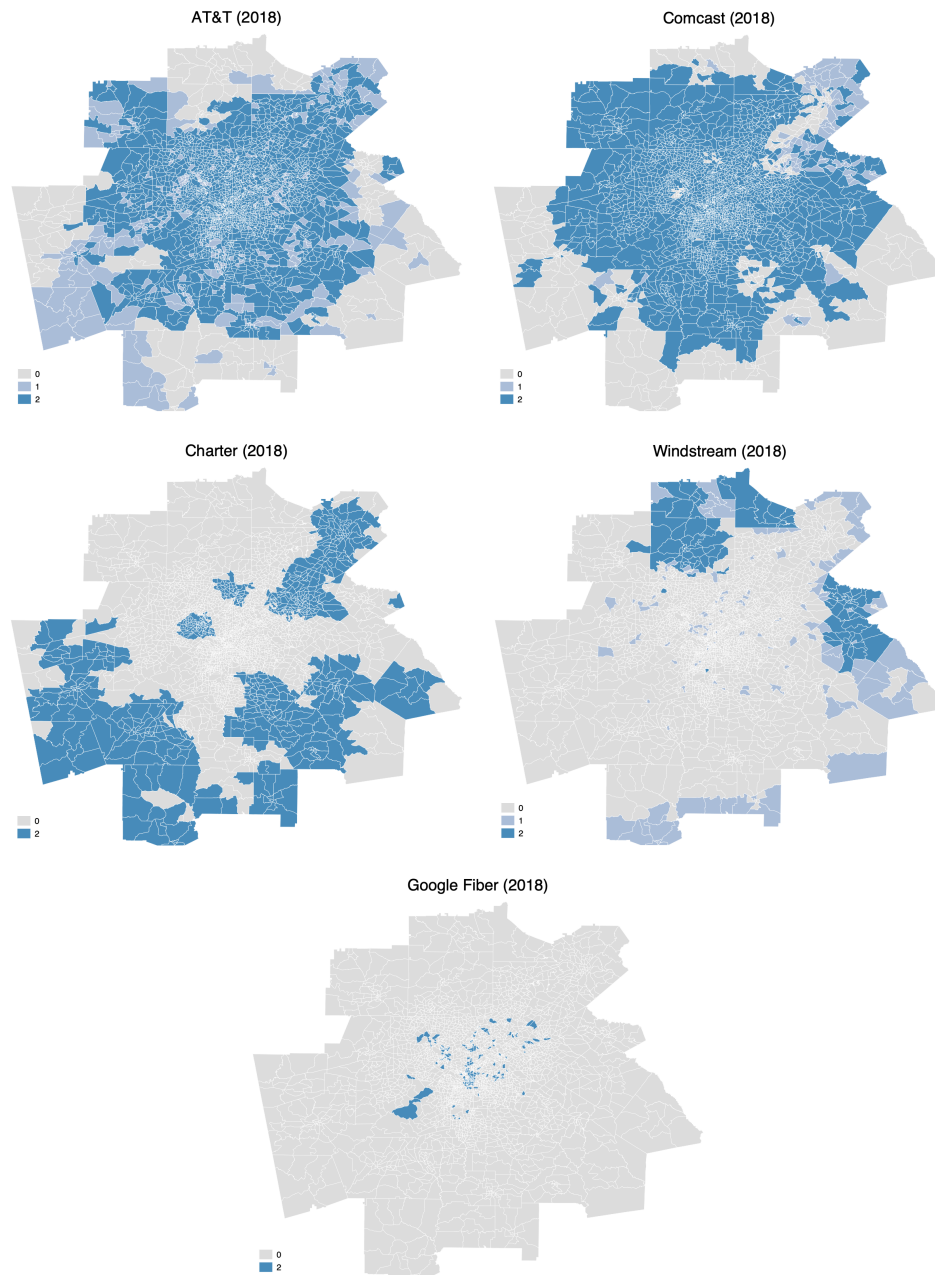


Figure 2A. No Competition ($\gamma = 0$)
Probability of Operating as Quality Level ($q = 2$)

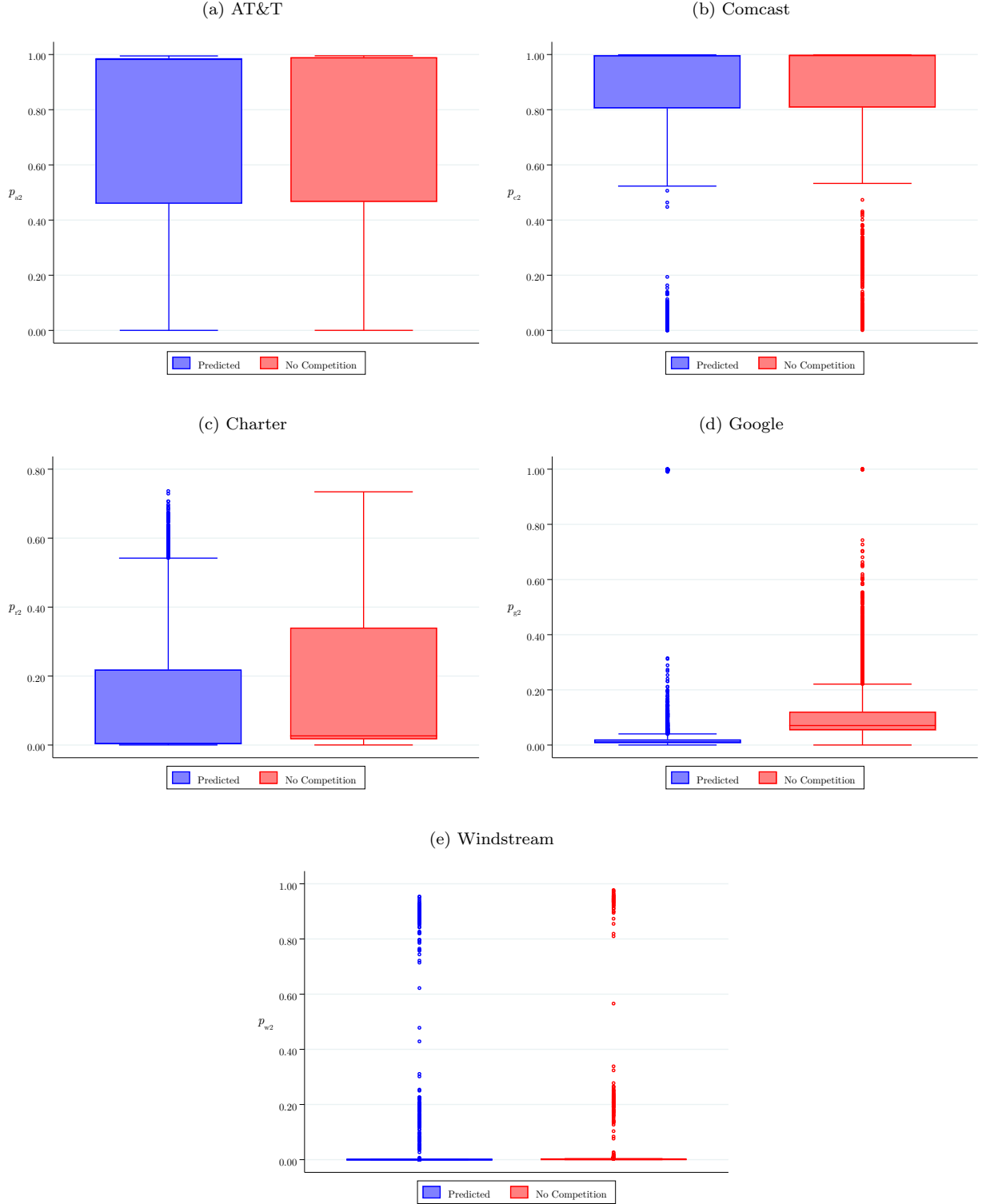
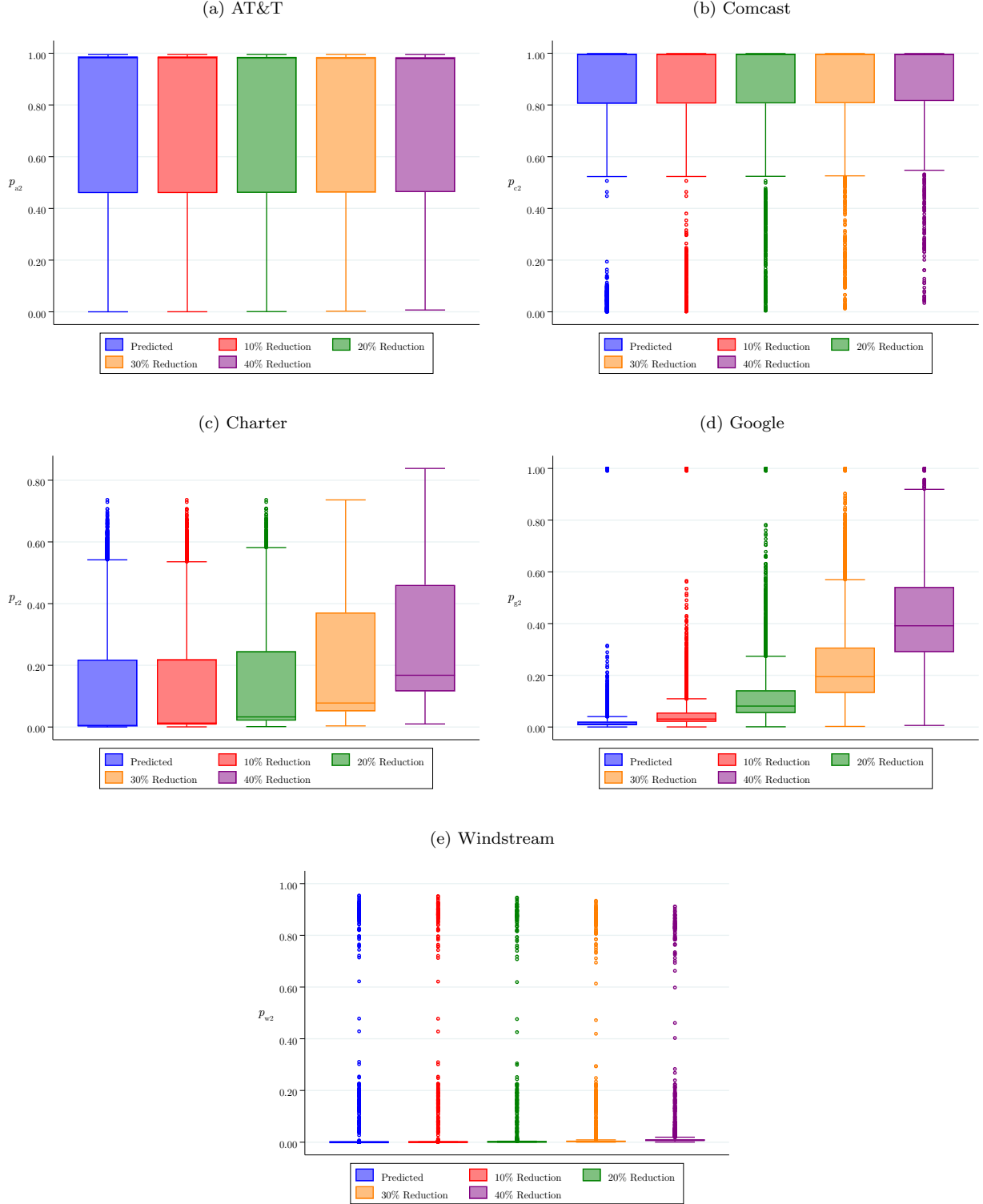


Figure 3A. Fixed Cost Reduction (θ_2^E)
Probability of Operating as Quality Level ($q = 2$)



B. Additional Tables

$$\text{Count } R^2 = \frac{\sum_{m=1}^M 1\{\hat{d}_m = d_m\}}{M}$$

$$\text{Efron's } R^2 = 1 - \frac{\sum_{m=1}^M (d_m - \hat{p}_m)^2}{\sum_{m=1}^M (d_m - \bar{d}_m)^2}$$

Table 1B. Full Game Fit Statistics

Outcomes	Count R^2	Efron's R^2
AT&T	0.873	0.556
Comcast	0.959	0.732
Charter	0.999	0.994
Google Fiber	0.978	0.627
Windstream	0.976	0.741
Overall	0.797	0.751

Table 2B. Stability of Equilibrium Check

Spectral Radius	
mean	0.039
sd	0.030
min	0.001
p5	0.014
p50	0.031
p95	0.088
max	0.380
count	2,687

Table 3B. Full Entry and Quality Game w/ Fixed Costs (2017)

	2-NPL	SEs	k-NPL	SEs
Quality Level: (q = 1)				
β_1 : Population (000)	-0.053	(0.051)	-0.042	(0.053)
β_1 : Per Capita Income (0,000)	0.075	(0.041)	0.074	(0.042)
β_1 : Land Area (miles ²)	-0.028	(0.006)	-0.030	(0.007)
α_1 : AT&T	4.299	(0.277)	4.281	(0.289)
α_1 : Comcast	5.573	(0.357)	5.582	(0.372)
α_1 : Charter	6.421	(0.383)	6.496	(0.406)
α_1 : Windstream	2.017	(0.317)	2.109	(0.349)
γ_{11}	0.929	(0.150)	0.913	(0.177)
γ_{12}	1.177	(0.163)	1.256	(0.201)
Quality Level: (q = 2)				
β_2 : Population (000)	0.204	(0.050)	0.205	(0.052)
β_2 : Per Capita Income (0,000)	0.177	(0.040)	0.173	(0.041)
β_2 : Land Area (miles ²)	-0.059	(0.008)	-0.060	(0.008)
α_2 : AT&T	6.007	(0.379)	5.947	(0.383)
α_2 : Comcast	8.560	(0.458)	8.524	(0.465)
α_2 : Google Fiber	8.139	(0.554)	8.090	(0.562)
α_2 : Windstream	2.412	(0.393)	2.382	(0.410)
γ_{21}	0.920	(0.154)	0.873	(0.178)
γ_{22}	0.981	(0.172)	0.959	(0.207)
Fixed Costs				
θ_1^E	9.483	(0.410)	9.463	(0.411)
θ_2^E	11.299	(0.501)	11.277	(0.506)
θ^D	1.692	(0.360)	1.683	(0.358)
θ^U	2.907	(0.298)	2.922	(0.297)
θ_1^n	-3.280	(0.358)	-3.321	(0.357)
θ_2^n	-1.628	(0.273)	-1.609	(0.274)
Log-Likelihood	-3,274.640		-3,281.877	
Markets	2,687		2,687	

Note (a): Observed information matrix standard errors in parentheses.

C. Equilibrium Analysis to Check Stability of Game

- System of Equations

$$\Psi_a(p_c) = \frac{\exp(X\beta + \alpha_a - \gamma p_c)}{1 + \exp(X\beta + \alpha_a - \gamma p_c)}$$

$$\Psi_c(p_a) = \frac{\exp(X\beta + \alpha_c - \gamma p_a)}{1 + \exp(X\beta + \alpha_c - \gamma p_a)}$$

- Jacobian Matrix

$$J(p_a, p_c) = \begin{bmatrix} \frac{\partial \Psi_a(p_c)}{\partial p_a} & \frac{\partial \Psi_a(p_c)}{\partial p_c} \\ \frac{\partial \Psi_c(p_a)}{\partial p_c} & \frac{\partial \Psi_c(p_a)}{\partial p_a} \end{bmatrix} = \begin{bmatrix} 0 & -\gamma p_a(p_a - 1) \\ -\gamma p_c(p_c - 1) & 0 \end{bmatrix}$$

- Find Eigenvalues of System

$$\det(J(p_a^*, p_c^*) - \lambda I) = 0$$

$$\det \left(\begin{bmatrix} -\lambda & -\gamma p_a^*(p_a^* - 1) \\ -\gamma p_c^*(p_c^* - 1) & -\lambda \end{bmatrix} \right) = 0$$

$$\lambda = \pm \gamma \sqrt{p_a^*(p_a^* - 1)p_c^*(p_c^* - 1)}$$

- System is stable if spectral radius, $\max |\lambda| < 1$.

- Full Game Jacobian Matrix

$$\Psi_{a1}(p_{c1}, p_{c2}) = \frac{\exp(\mathbb{E}[\bar{\pi}_{a1}])}{1 + \exp(\mathbb{E}[\bar{\pi}_{a1}]) + \exp(\mathbb{E}[\bar{\pi}_{a2}])}$$

$$\Psi_{a2}(p_{c1}, p_{c2}) = \frac{\exp(\mathbb{E}[\bar{\pi}_{a2}])}{1 + \exp(\mathbb{E}[\bar{\pi}_{a1}]) + \exp(\mathbb{E}[\bar{\pi}_{a2}])}$$

$$\Psi_{c1}(p_{a1}, p_{a2}) = \frac{\exp(\mathbb{E}[\bar{\pi}_{c1}])}{1 + \exp(\mathbb{E}[\bar{\pi}_{c1}]) + \exp(\mathbb{E}[\bar{\pi}_{c2}])}$$

$$\Psi_{c2}(p_{a1}, p_{a2}) = \frac{\exp(\mathbb{E}[\bar{\pi}_{c2}])}{1 + \exp(\mathbb{E}[\bar{\pi}_{c1}]) + \exp(\mathbb{E}[\bar{\pi}_{c2}])}$$

$$J(p_{a1}, p_{a2}, p_{c1}, p_{c2}) = \begin{bmatrix} \frac{\partial \Psi_{a1}}{\partial p_{a1}} & \frac{\partial \Psi_{a1}}{\partial p_{a2}} & \frac{\partial \Psi_{a1}}{\partial p_{c1}} & \frac{\partial \Psi_{a1}}{\partial p_{c2}} \\ \frac{\partial \Psi_{a2}}{\partial p_{a1}} & \frac{\partial \Psi_{a2}}{\partial p_{a2}} & \frac{\partial \Psi_{a2}}{\partial p_{c1}} & \frac{\partial \Psi_{a2}}{\partial p_{c2}} \\ \frac{\partial \Psi_{c1}}{\partial p_{a1}} & \frac{\partial \Psi_{c1}}{\partial p_{a2}} & \frac{\partial \Psi_{c1}}{\partial p_{c1}} & \frac{\partial \Psi_{c1}}{\partial p_{c2}} \\ \frac{\partial \Psi_{c2}}{\partial p_{a1}} & \frac{\partial \Psi_{c2}}{\partial p_{a2}} & \frac{\partial \Psi_{c2}}{\partial p_{c1}} & \frac{\partial \Psi_{c2}}{\partial p_{c2}} \end{bmatrix}$$

$$= \begin{bmatrix} 0 & 0 & p_{a1}(-\gamma_{11} + \gamma_{11}p_{a1} + \gamma_{21}p_{a2}) & p_{a1}(-\gamma_{12} + \gamma_{12}p_{a1} + \gamma_{22}p_{a2}) \\ 0 & 0 & p_{a2}(-\gamma_{21} + \gamma_{21}p_{a2} + \gamma_{11}p_{a1}) & p_{a2}(-\gamma_{22} + \gamma_{22}p_{a2} + \gamma_{12}p_{a1}) \\ p_{c1}(-\gamma_{11} + \gamma_{11}p_{c1} + \gamma_{21}p_{c2}) & p_{c1}(-\gamma_{12} + \gamma_{12}p_{c1} + \gamma_{22}p_{c2}) & 0 & 0 \\ p_{c2}(-\gamma_{21} + \gamma_{21}p_{c2} + \gamma_{11}p_{c1}) & p_{c2}(-\gamma_{22} + \gamma_{22}p_{c2} + \gamma_{12}p_{c1}) & 0 & 0 \end{bmatrix}$$