Quality Competition in the Broadband Service Provision Industry

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Abstract
We conduct an empirical analysis of quality competition between broadband Internet Service Providers (ISPs), using National Broadband Map data for 2011-2013 for almost a thousand local markets in California. We examine how incumbent ADSL firms respond to competition from CLECs and cable modem service providers. We use an important quality attribute, the downstream data rate, and estimate the strategic choice of quality for broadband ISPs.

Our paper follows a static game theoretic approach to the profit maximization decision of a broadband provider that leads to a simple two-stage method of estimation of the structural parameters of the ISPs' profit functions. The method accounts for both the strategic aspect of each firm's quality decision, as well as the endogeneity problems inherent in the estimation problem.

Our results include two main findings. First, ILECs improve the quality of their ADSL offerings when a cable player enters the market, and also when cable operators start to offer DOCSIS 3.0 speeds. Second, ILEC ADSL providers do not raise their service quality in response to ADSL competition from CLECs, but they do boost their speed when CLECs deploy fiber in the market. This research represents the first step in what we hope to be a major advance in the empirical analysis of broadband provision, where little structural econometric work has been done.

I. Introduction

Empirical studies to assess the relationship between competition in service provision and the quality of service offered to consumers are few. Furthermore, much of the scant empirical work that examines the broadband Internet Service Providers' (ISPs') choice of quality is not based on rigorous microfoundations for the firm's strategic decisions for entry and quality choice.

The objective of our study is to conduct an empirical analysis of quality competition among ISPs. We take advantage of recent advances in the industrial organization literature on feasible estimation of discrete games to model and estimate the determinants of an ISP's decision to enter a local market, and what speed of service to offer upon entry. Our research goal is to characterize the fundamentals of broadband services provision in the US with a structural model, allowing us to address various hypotheses concerning how firms respond to the entry and quality decisions of their rivals. The model will eventually allow us to address how competition would evolve under various policy counterfactuals that affect competition, although we do not pursue that in this preliminary version of the paper.

Acronyms

ADSL	Asynchronous Digital Subscriber Line
AME	Average Marginal Effect
CBG	Census Block Group
CLEC	Competitive Local Exchange Company
CPUC	California Public Utility Commission
DOCSIS	Data Over Cable Service Interface Specification
DSL	Digital Subscriber Line
FIRE	Finance, Insurance, and Real Estate
FTTN	Fiber to the Node
ILEC	Incumbent Local Exchange Company
IO	Industrial Organization
ISP	Internet Service Provider
Kbps	Kilobits per second
KF	Kilofeet
MADTR	Maximum Advertised Downstream Transmission Rate
Mbps	Megabits per Second
ME	Marginal Effect
MEMdn	Marginal Effect at the Median
MLE	Maximum Likelihood Estimation
NBM	National Broadband Map
SE	Standard Error
TV	Television

Our econometric model draws on the work of Bajari, et al. (2010), who propose a two-stage method to estimate models of strategic interactions for discrete strategy spaces. In the first stage, we estimate reduced form choice probabilities for the entry and quality decision of each potential entrant in a market. The estimated choice probabilities are then used in the second stage to estimate the structural parameters of the firms' profit functions. The method thus accounts for both the strategic aspect of each firm's decision, as well as the endogeneity problems inherent in estimation.[1]

In this first version of our paper, we focus on competition in nearly a thousand local broadband markets in California, although eventually we will extend the analysis to the entire US. The markets are small geographic areas around central offices[2] of Incumbent Local Exchange Companies (ILECs). In these markets, we examine how ILEC ADSL[3] players respond to competition from Competitive Local Exchange Companies (CLECs) and cable players. We focus on an important quality attribute, the Internet data rate, and estimate the strategic choices of maximum advertised download data rates for ILEC broadband ISPs. We draw our firm count and speed data from five waves of the US National Broadband Map (NBM).

The economic literature on competition and quality shows that a higher degree of market competition may lead to higher or lower quality of service. While more competition increases the firm's incentives to supply high quality (holding output prices fixed), more competition also reduces the price–cost margin, which reduces the incentives to invest in quality. Considered another way, if greater competition leads to stronger share-stealing effects, there will be higher equilibrium quality. However,

[1] The endogeneity problem arises from the familiar simultaneity problem in incomplete information games: in equilibrium, the competitors' actions depend on their expectations about the firm's action, and vice versa.

[2] A central office (or "wire center") is the location where the telephone company's network switching equipment is installed. There is one central office for each local telephone exchange in the traditional Public Switched Telephone Network (PSTN).

[3] Asynchronous Digital Subscriber Line (ADSL) is a technology that enables broadband data transmission over the copper telephone lines in the local loop of the telephone exchange. ADSL service, as defined for purposes of the National Broadband Map and therefore this study, may involve use of copper lines all the way from the central office to the subscriber's premises, or may make use of fiber from the central office to a remote terminal. The common element is that ADSL involves using the copper telephone wires for the last part of the transmission path to the subscriber's premises. ADSL offers faster download than upload speed, as opposed to symmetric DSL (SDSL). SDSL is primarily a business product.

given that the elasticity of demand with respect to quality need not increase with competition, the premise may not hold. Thus, the net effect of competition on quality is a priori uncertain and empirical measurement is necessary. Outside of a few markets such as healthcare, airlines, and retail gasoline, this has rarely been done in the literature.

Our paper contributes to the existing literature by showing empirically that ILECs appear to respond to intermodal but not intramodal competition. ILECs improve the quality of their ADSL offerings when a cable operator enters the market, or when the incumbent cable operator deploys DOCSIS 3.0. We also found evidence that ILECs do not raise their ADSL service quality when the competing CLEC is offering ADSL only, regardless of speed, but that ILECs do boost their speed when CLECs deploy fiber in the market.

Future work will investigate how CLEC ADSL and cable modem players respond to intermodal and intramodal competition. Our future analyses will also include competition from fixed and mobile wireless broadband. Our results will shed light on whether policymakers should encourage more intramodal competition, for example, by easing entry through unbundling of local network elements or policy prohibiting exclusive video and internet franchises by localities. In addition, we can also assess the efficacy of the US strategy of encouraging mostly intermodal competition (DSL and fiber offered by AT&T and Verizon vs. cable modem service offered by Comcast and other CATV providers). The research represents the first step toward a major advance in the empirical analysis of broadband provision, where little structural econometric work has been done.[4]

The next section reviews the literature on competition and quality and provides an overview of the literature on entry games with a special focus on static games. Section III details the data, and

[4] The main structural contribution is by Nevo et. al. (2013), who examine the welfare effects from usage-based pricing and demand for residential broadband.

Section IV describes the empirical model. Results are presented in Section V. Section VI concludes with discussion of the results and outlines our plans for future work.

II. Background and Review

A. Competition and Quality

The relationship between competition and quality has attracted much recent attention from US policy makers. In particular, the education, electricity, finance, health, media and telecom sectors have experienced extensive legislative reform by state and federal governments intended to promote consumer choice, greater product variety, and increased quality through greater competition. In his examination of healthcare, Katz (2013) explains the key justification for this approach as being the "…intuition that, due to the potential to steal market share from rivals, a competitive care provider has stronger incentives to raise its quality to attract patients." Furthermore, this intuition is conditioned on the "belief that greater competition leads to stronger share-stealing effects and, thus, higher equilibrium quality." In this section we consider the theoretical and empirical evidence concerning this intuition.

1. Theoretical literature on competition in quality

The straightforward intuition that share stealing will lead to a positive association between competition and quality is supported by economic theory when prices are fixed, as is the case for some regulated markets (e.g., Douglas and Miller, 1974; Schmalensee, 1977). As long as the fixed price is set above marginal cost at some base level of quality, firms will increase quality in an attempt to gain market share.

When prices are not fixed, more competition will also lower the price–cost margin and this may reduce the incentives to invest in quality. Gaynor (2006) uses the Dorfman-Steiner (1954) condition, adapted to monopolistic competition, to show that the amount spent on quality by the firm depends on the ratio of the quality elasticity of demand to the price elasticity of demand. When an increase in market power reduces both elasticities, quality may increase or decrease depending on the relative strengths of the two effects. Gaynor notes that similar intuition is provided by several other studies but within a different modeling framework. For example, Kranton (2003) studied the effect of competition on quality when consumers are imperfectly informed about quality. Her model shows that if firms compete in price for market share, both price and quality can be lower, which is analogous to the price elasticity of demand exceeding the quality elasticity of demand.

Matsa (2011) describes the tradeoffs facing the firm in the short and long run. He notes that lower profit margins under more competition reduce the immediate cost of losing a "sale" so firms may shade quality. In the long run, however, competition may raise the likelihood that unhappy consumers switch to a competitor, so firms improve quality. In their growth model with incremental innovations, Aghion and Howitt (2009) show that competition fosters innovation in sectors where firms operate at the same technological level. Here, competition reduces pre-innovation rents and thereby increases the incremental profits from innovating and becoming a leader. In other sectors, competition reduces the post innovation rents of laggard firms and thus their incentive to catch up with the leader. Chen and Schwartz (2013) also use a model of innovation to outline conditions where the incentive to add a new, higher-quality product can be greatest under monopoly. The monopolist loses more profit on the old product but may earn more profit on the new one because it prices the old product in a way that internalizes the effect on the new one.[5] While these studies represent only a few examples, they are

[5] The key factor is the extent to which the monopolist can divert sales to the new product as opposed to leaking sales to outside goods if it raises the price of its old product (Chen and Schwartz, 2013).

illustrative of the overall finding from the theoretical literature. Competition can lead to lower or higher quality, depending on the underlying properties of demand, costs and information.[6]

2. Empirical literature on competition in quality

Given the theoretical ambiguity in outcomes, it is not surprising that recent empirical studies have produced mixed results on the relationship between competition and quality for different industries with different market conditions. The basic empirical approach has been to write down a firm's equilibrium quality function as the implicit solution to their profit maximization problem. A reduced-form quality equation is then specified that relates some measure of quality to cost and demand shifters and to a measure of the number of firms in the market. For example, Mazzeo (2003) shows that average flight delays are longer in more concentrated airline markets. Goolsbee and Petrin (2004) estimate that cable television (TV) channel capacity, number of over-the-air channels and number of premium movie channels increased in response to satellite entry, while Savage and Wirth (2005) document a similar effect with respect to potential entry from cable overbuilders.[7] Matsa (2011) finds that supermarkets facing more intense competition have more products available on their shelves, while Olivares and Cachon (2009) show that the inventories of General Motors dealerships increases with the number of competitors.

In contrast, Domberger and Sherr (1989) find no correlation between the threat of new entry and customers' satisfaction with their attorney used for home purchases. Prince and Simon (2013) show

[6] This ambiguity has a long history in industrial organization (IO) theory. Chamberlin (1933) and Abbott (1955) show that firms with market power may reduce product quality to save costs and maximize their profits. Swan (1970, 1971) demonstrated no relationship between monopoly power and product quality and defined conditions under which a competitive and monopoly market introduce a product with the same level of quality but the monopoly will charge a higher price. Schmalensee (1979) shows that this result holds up under some relaxation of the original assumptions but questions whether quality choice under oligopoly will be well approximated by either the competitive or monopoly models.

[7] An overbuilder in the cable industry is a second entrant into an existing cable franchise area to compete with the incumbent. Overbuilding using hybrid fiber-coax networks (i.e., a traditional cable system architecture) is relatively rare in the US in general and in California in particular.

that flight delays for incumbent airlines worsen in response to entry threats by Southwest Airlines. Chen and Gayle (2013) examine mergers and product quality (i.e., the ratio of non-stop flight distance to total flight distance used to get passengers from origin to destination) for the airline industry. They find that quality increased in markets where the merging airlines did not compete *ex ante*, and decreased in markets where they did. This is consistent with their theory that mergers improve coordination but diminish competitive pressure for firms to provide high quality products.

Similar studies have also been conducted with advertising as the proxy for quality. Dick (2001) examined the US retail banking industry using higher advertising intensity (i.e., marketing expenses divided by total asset value) as a measure of higher customer service quality. He found that dominant banks provide a higher level of service quality than fringe banks. Crawford (2007) analyzed the relationship between TV station ownership and the quality of their programming. He found no relationship between cross ownership with a local newspaper or radio station and the number of minutes of advertising included in TV programming, where more minutes indicating lower quality TV service. Hiller et al. (2014) analyzed consumer media bundles and showed a positive correlation between the number of independent TV stations and the amount of time and space devoted to advertising.

In telecommunications, Wallsten and Mallahan (2013) find that the number of wireline ISPs in a US census tract is positively correlated with the highest advertised downstream speeds. Nardotto et al. (2012) show a positive relationship between lower barriers to entry, measured by the presence of local loop unbundling, and average broadband download speeds in the United Kingdom.[8] Molnar and Savage (2013) show that wireline speeds are higher in census block groups with two or more wireline ISPs than

[8] Unbundling requires the incumbent telephone company to lease the connection from their central office to the household ("local loop") to new entrants so they can compete in the final product market for broadband Internet.

with a single wireline ISP, but there is no relationship between wireline speeds and the number of wireless ISPs.

While reduced-form quality equations provide useful insights into the general relationship between competition and quality, they say nothing about the strategic interactions between firms with respect to their quality choices. Kugler and Weiss (2013) use a reaction-function approach to estimate the strategic quality choices for Austrian gas stations. Their empirical reaction function relates the opening hours of a station to those of its competitors. Their results suggest significant but imperfect coordination, in opening hours among stations of the same network, which implies that opening hours are strategic complements. They find a similar but weaker effect between independent stations or stations from competing networks. Brueckner and Luo (2013) use a similar model to investigate strategic interaction among US airlines in flight frequency. Using instrumental variables estimation, a positive reaction function is found in some specifications, suggesting complementarity in the choice of frequencies.

In summary, there is much work in the field of Industrial Organization (IO) on the effect of competition on prices, but not nearly enough has been done on quality. Both parties to a merger law suit would benefit from some empirical evidence in this direction. Lack of evidence on this is mostly due to the lack of data on quality. Schmalensee (1979) noted 35 years ago that "it is far from obvious that any single mathematical representation of quality can serve for a broad spectrum of products." Even more so today, most industries sell highly differentiated products, making standardized quality measures difficult to collect, and the few previous studies looked at flight delays, product availability in supermarkets, and the number of TV channels. These are worthwhile quality dimensions in their respective industries, but pale compared to the importance of Internet speed in the broadband industry. This paper investigates an essential and standardized quality attribute – Internet speed in a highly relevant industry in the digital age – and estimates the strategic choices of download and upload speeds for Californian broadband providers. Estimation of the static model of strategic interactions with discrete-choice methods determines the probability of a particular level of quality for a representative broadband provider as a function of the expected quality choice of rivals and various market characteristics.[9]

B. Broadband Market Entry

When entering new markets, or re-evaluating their business plans regarding technology or quality in an existing market, ISPs face many decisions: which technologies to offer, what packages to create, how much to invest in service quality, what prices to charge, and how to promote service offerings. The ISP's customers can decide on the type of contract, what service level they purchase, and what additional products they take with a service bundle. ISPs must also consider the strategic reactions of the rival firms. Will they enter the market? How will a competing firm position its market play? The interrelated nature of these decisions suggests modeling them with empirical discrete games that can assume sequential or simultaneous move by the players.

We model the broadband Internet markets as a repeated simultaneous game. Simultaneous games are imperfect-information games; players do not have the knowledge about the actions of the others. In our model, ISPs choose a quality simultaneously, and they do not know the current-period actions of the other firms.[10] When we observe broadband markets and make an attempt to understand how the players behave, we also lack information on price, cost, or demand data. We can observe,

[9] Xiao and Orazam (2011) estimate a simple discrete-choice model of broadband entry and find that sunk costs are an important determinant of wireline entry in US zip codes. However, they are unable to distinguish between one, two or three providers due to data confidentiality, and they do not estimate the direct effects of entry on market outcomes such as quality.

[10] The reality is, or course, more complex; ISPs do not actually choose a service quality once per six months all at the same time. However, our modeling approach is commonly adopted in the literature when there is no clear first mover and is best seen as an approximate structure designed to reflect uncertainty regarding competitors' plans.

however, the entry and exit of players, the speeds that they provide, along with market demographics, and make inferences even in the case of incomplete information.

Inference about structural parameters of the profit function from observations on entry was made possible by Bresnahan and Reiss (1990) and the subsequent stream of literature triggered by their seminal paper. Bresnahan and Reiss inferred the effects of entry on competition from the relationship between the number of market entrants and the market size. By observing strategic entry decisions of small retail firms in isolated rural markets, they argued that firms must pay a fixed and sunk cost to enter the market. They also argued that the total industry profit depends on the number of firms on the market but not on the identity of the entrants. Bresnahan and Reiss proposed an estimator that maximizes the likelihood for the number of firms and introduced the idea of entry thresholds, i.e., the market size required to support a given number of firms. The two main disadvantages of their model are that firms' costs are homogenous, and that the firms do not offer differentiated products. In their later work (1994), they estimated firms' sunk costs from differences in the thresholds for entry and exit.

Berry (1992) relaxes this limitation by allowing heterogeneity between firms entering the markets. He develops a model of market entry considering a large number of heterogeneous potential entrants and applies the model to analyze competition in airline markets. Berry recommends using simulation methods to address the computational problem of calculating the linear combination of integrals that define the probability of events. Mazzeo (2002) extends the Bresnahan-Reiss model by allowing firms to offer heterogeneous (high-quality and low-quality) products. Using data from motel markets along US interstate highways, and endogenizing the quality choice of firms, he founds that hoteliers have strong incentives to differentiate. Ciliberto and Tamer (2009) broaden the literature by allowing for heterogeneity without making equilibrium selection assumptions. Applying a pseudo maximum likelihood estimation method to the US airline industry, and expanding on Tamer's earlier work (2003), they find evidence of heterogeneity across airlines in their profit functions.

Additional recent contributions include Seim (2006), Aguirregabiria and Mira (2007), and Bajari et al. (2010). Seim's static equilibrium model makes early use of spatial econometrics in market structure and product type choice studies. Her simulation results demonstrate the firms' incentives for spatial differentiation in the video rental industry and the importance of incorporating product-type choices into the market entry process. Aguirregabiria and Mira (2007) propose a two-step method to estimate static games of incomplete information and illustrate it using an example of a static game of market entry. Their method greatly reduces the computational complexity of earlier approaches, and the present work derives from theirs. In the spirit of Aguirregabiria and Mira (2007), Bajari, et al. (2010) implement a two-stage method to estimate models of strategic interactions for discrete strategy spaces. In the first stage, they estimate reduced form choice probabilities for the entry and quality decision of each potential entrant in the market. Then, in the second stage, they use these computed choice probabilities to estimate the structural parameters of the firm's profit function. As an application for the two-stage model, they study the determination of stock recommendation issued by equity analysis for high-tech stocks between the years of 1998-2003.

In telecommunications, employing the entry model in Mazzeo's (2002) study, Greenstein and Mazzeo find (2006) evidence that competitors are heterogeneous and that firms account for both potential market demand and the business strategies of their competitors when making their entry decisions. Following Bresnahan and Reiss (1991), Xiao and Orazem (2011) estimate a discrete-choice model of broadband entry, as discussed above.

In addition to these two works, in which estimation is based directly on theoretical entry models, most studies of market entry in broadband are nonstructural (reduced-form). Almost all of the existing works have been extracted from cross-sectional, static studies of existing players; the impact of potential new entrants are not studied. In a typical broadband market entry study, a cross-section of either the number of ISPs or an indicator for the presence of at least one competitor in the local area is regressed on demographic and other market characteristics (Prieger, 2003; Grubesic and Murray, 2004; Flamm, 2005; Prieger and Church, 2012; Prieger, 2013). These studies show that the decisions of telecom service providers to deploy network resources and offer service in a local market depend on both economic and regulatory considerations. Demand factors such as market size, average income, and other demographic characteristics all been shown to affect broadband penetration (Prieger, 2003; Grubesic and Murray, 2004; Flamm, 2005; Flamm and Chaudhuri, 2007; Prieger and Hu, 2008; Prieger, 2013). Some of these papers also show that population density or terrain also influence broadband penetration in the expected ways, and can be used as proxies for cost. For example, rural areas are more likely to be served only with lower-speed broadband or by few providers, or less likely to have broadband available at all than urban areas, due to low population density and rougher topography, (Stenberg et al., 2009; Li et al., 2011; Prieger, 2013). Intermodal and intramodal competition among broadband ISPs, both actual and potential, also affects the incentives to enter the local markets (Denni and Gruber, 2007; Prieger and Hu, 2008; Wallsten and Mallahan, 2013).

Like the work of Greenstein and Mazzeo (2006) and Xiao and Orazem (2011), we perform structural estimation to identify parameters of the potential entrant's profit function. Unlike the earlier studies, we are particularly interested in those parameters relating to quality competition. We hope that our work will thus be a significant addition to the scant structural empirical work on broadband competition.

III. Data

In this paper, we focus on competition in broadband service provision in local markets in California. We chose California because it is large enough to contain many local markets, yet not so large as to make working with the voluminous NBM data unwieldy. In future versions of the paper, we hope to expand to other states.

A. Market definition

Any definition of the broadband Internet market is only an approximation of how ISPs may view their market play. Market definition is made difficult because the natural areas of deployment for different types of broadband providers, e.g., wire center serving areas and cable franchise areas, do not exactly match. Previous studies have used counties, census tracts, ZIP codes, and local telephone exchange boundaries to define the geographical market for broadband Internet (Gillett and Lehr, 1999; Prieger, 2003; Wallsten and Mallahan, 2013; Xiao and Orazem, 2011; Nardotto et. al., 2012; Prieger and Conolly, 2013; Prieger, 2013). Our market definition instead is similar in spirit to that of Prieger and Hu (2008b), who carefully examine the distance from the local phone company's central office to define the local markets for ADSL. Roughly speaking, our 965 broadband Internet markets are small geographic areas within the distance of 2.3 miles of the ILECs' central offices in California.[11] The main reason behind our market definition is that in areas close to an existing ILEC wire center, the incumbent ADSL player has the greatest ability to match the speeds of fiber and cable modem competitors, due to the degradation of DSL speed with line distance. The rest of this subsection gives further details on the market definition process and can be skipped by readers not interested in the technical details.

Our definition of the markets for the entry game is a three-step process. Market definition begins with drawing a circle of radius 12,000 feet (12 kilofeet (kf), about 2.3 miles) around each California ILEC wire center found in the NECA tariff #4. The threshold of 12 kf (along with a secondary threshold of 18 kf, discussed below) was chosen in accord with California Public Utility Commission methodology for validating information on the provision of DSL (CPUC, 2013). A radius of 12 kf from the equipment in the wire center also corresponds to the straight-line threshold for provision of DSL at 6.3

[11] For robustness, we also studied markets with a circle of radius of 18 thousand feet from an existing central office, and will also show results using this geographical delineation as well.

Mpbs.[12] Since last-mile network may be constrained to run along right-angled streets, a 12 kf radius by the Euclidean metric has a worst-case situation where the lines from the wire center have a taxicab distance of 18 kf long,[13] in which case DSL of at least 1.5 Mbps is possible. These speed limitations are relaxed in many markets by the installation of remote terminals to neighborhoods farther from the wire center, as in AT&T's fiber-to-the-node (FTTN) architecture for its U-verse service. However, we have no data on which markets include remote terminals.

In a second step, we limit the areas defined by the circles to actual wire center serving areas of the ILECs. Using GIS data from GDT on the service territory of the ILECs associated with each wire center, parts of the 12 kf radius circles not also in the actual service territory were excluded from each market. This step ensures that in dense urban areas, where wire centers are closer to each other, the market area associated with one wire center does not overlap with the territory served by an adjacent wire center.[14]

A third step is necessary to match the second-step market areas to the broadband provision data in the NBM, which is keyed to Census geography. The third-step market area, therefore, consists of the union of all Census block groups (CBGs) that lie wholly within an area from the second step. In a few rural locations, no CBG are contained within the areas from step two, and in such cases we instead use the set of CBGs that overlap the step-two area. All GIS processing for market definition was performed

[12] For the relationship between distance and ADSL speed, see http://whatis.techtarget.com/reference/Fast-Guide-to-DSL-Digital-Subscriber-Line.

[13] The taxicab distance, defined as the distance between two points measured along axes at right angles, is also called Minkowski's L_1 distance. The worst-case scenario is the maximum taxicab distance for a fixed Euclidean distance, and occurs when the communications lines run along the legs of a right triangle with hypotenuse equal to 12 kf in length. The line length to reach the 12 kf radius is about 16.97 kf in this case.

[14] In a few markets (29) the purported coordinates of the wire center from the GDT and NECA data sources did not agree to within 2 V&H units (about 0.6 miles) using the L2 norm. (The telephone industry uses a unique "V&H" coordinate system for central office locations.) For such wire centers we did not use the GDT wire center serving area to limit the market. Instead we used the entire area defined by the 12 kf radius around the wire center (as located using the NECA data) less any area already part of another market.

using ArcMap. The market definitions result in 965 markets.[15] For use in testing the robustness of the econometric conclusions, an equivalently constructed set of markets based on an 18 kf (about 3.4 miles) radius were also created.

In summary, our definition results in a set of local broadband markets that are distinct, small enough to represent an ILEC's decisions about infrastructure in a single wire center area for DSL, yet large enough so that local decisions about infrastructure and quality of service do not affect multiple markets.[16] Figure 1 shows the step-two and step-three market areas throughout the state. In Figures 2 and 3 we show a detailed view of some of these markets. The first figure shows some of the Los Angeles urban area, in which the markets are often constrained more by wire center boundaries than by the 12 kf radius. This is most apparent in the West L.A. markets in the upper left and the downtown L.A. markets in the upper right areas of the figure. The heavy dots on the map mark the ILEC central office locations, the blocky areas surrounding the points are the market areas from step three (each a collection of CBGs), and the larger, circular or smooth-bordered areas are the market areas from step two (the intersection of the 12 kf and wire center area boundaries). The other figure shows some extremely rural markets. A few markets at the top of Figure 3 are like those in Figure 2, where at least one CBG falls entirely within the step-two market area. The large markets in the middle of Figure 3 show examples of the few markets composed of CBGs that overlap with the step-two market area (because no CBG is wholly contained within it). These CBGs with low population density can be quite large, and this accounts for much of the rural areas in the right panel of Figure 1 being colored in. This is not likely to lead to overstating broadband presence, however. Whether an extremely rural central

[15] Four of the potential market areas were dropped after the second step because they were very small, and an additional market defined for a wire center on the Oregon border was dropped because it appeared to serve customers in Oregon instead of California.

[16] By which we mean infrastructure deployment in the central office and within the same wire serving area. Of course, backhaul infrastructure such as high capacity transmission lines between central offices or connections to the Internet backbone may affect multiple markets.

office is placed into a large or small market area, the maximum speed of any broadband provision of any type is highly likely to be present near the central office, which is typically in the center of town.

B. Broadband data

We draw data on the location and quality of broadband service in California from five semiannual waves of the US National Broadband Map, June 2011 to June 2013.[17] These were the latest data available at the start of this project. We chose not to include the first two rounds of the NBM data, from 2010, because those rounds used an earlier Census geography. We matched ISPs offering service anywhere in the market areas to the corresponding markets and recorded each firm's maximum advertised downstream rate, separately by technology and holding company.[18] While in theory the NBM also records actual transmission rates, those fields are missing for many firms, and we use the advertised rates instead. Technologies covered in the NBM include the ADSL, fiber, and cable modem services we investigate in this version of the paper, as well as wireless and less commonly used wireline technology.

In general, information on potential entry that did not occur cannot be found in the NBM. However, since the markets are defined around ILEC locations, the ILEC ADSL potential entrant is obvious. The ADSL quality choices of ILECs in California markets are shown in Figure 4. The data include 14 ILECs in 965 markets over four periods, choosing among five quality alternatives, for a total of 3,860 cases and 19,300 observations available for the estimations. The first-stage estimations include observations for 25 cable companies (4,365 cases and 26,190 observations) and 16 CLECs (37,743 cases

[17] Created from a collaboration between the National Telecommunications and Information Administration, the FCC, and all states, territories and Districts of the US, the NBM is an online tool that provides semi-annual information on the broadband service providers, their product type, technology, and their maximum advertised upload and download speeds in each US census block.

[18] Service providers are aggregated to the level of their holding company, even if they operate in the same market with multiple operating companies. We used a master list of holding companies constructed by one of the authors for previous broadband research that includes all firms appearing in the FCC Form 477 broadband filings in recent years. Our list of holding companies account for variation in company names, mergers, acquisitions, spin-offs, and cable system area swaps.

and 226,458 observations for ADSL; 52,234 cases and 313,404 observations for fiber). The set of potential entrants for CLECs for a market and technology type includes any CLEC offering service anywhere in California (except when the CLEC is already an ILEC in the market). The set of cable modem entrants includes any firm with a franchise area that at least partially overlaps a market.

For cable firms, the locations for entry into broadband service provision is limited by the extent of their franchise areas. In California, new cable franchises are awarded by the state, and the CPUC makes available GIS shapefiles of state-franchised areas.[19] We used these data to construct a variable measuring what fraction of the market area is covered by the franchise area. In one of our robustness tests, we weight the cable modem competition variables by this variable to account for market coverage that is less than complete.

C. Demographic data

Most of the demographic data for the markets come from Geolytics, based on the 2010 Census and 2008-2012 American Consumer Survey data from US Census Bureau for CBGs. However, to improve the precision of the population and household density variables, we instead counted population and households in Census blocks falling into our step-two market areas, and divided each by the step-two market area in square miles.[20] Similarly, the regressor for market area is for the step-two definition. We used the County Business Patterns 2011 data of the US Census Bureau to get information on finance,

[19] Not all franchise areas were awarded by the state in the past, however. Some legacy locally-awarded franchise areas with long terms are missing, and the fraction coverage variables described below in the text are missing for those. As local franchises expire, they are converted to state franchises.

[20] This avoids the difficulty that some of the step-three market areas are overly large in rural areas, even though the locus of economic activity is near the central office. If we included population and area of the entire step-three market areas, the resulting densities would be misleadingly low.

insurance, and real estate (FIRE) employment in our markets.[21] Table 1 contains summary statistics for the variables used in the study.

IV. The Econometric Model

A. Game-theoretic underpinnings

Our structural econometric model is based on a static game theoretic approach to the profit maximization decision of a broadband provider. We adopt the approach of Bajari et al. (2010) for estimation of static games of incomplete information with multiple equilibria, and we refer the interested reader to their article for presentation of the model at a high level of mathematical formality. The static game approach is a generalization of a discrete choice model that allows the quality choice of a firm to depend on the actions of the other firms. Firm *i* in market *m* at time *t* chooses an alternative $a_{imt} \in A = \{0,\ldots,J\}$ representing a quality level, where alternative 0 represents offering no broadband at all. Let the firm's profit u_{imt} be

$$u_{imt}(a_{imt}, a_{-imt}, s_{imt}; \theta) = \pi_{imt}(a_{imt}, a_{-imt}, s_{imt}; \theta) + \epsilon_{imt}(a_{imt}) + \eta_{imt}$$

where a_{-imt} represents the actions (chosen alternatives) of the other potential entrants in the market and period, s_{imt} is a vector of firm *i*'s state variables affecting profit, and θ is a finite vector of parameters. The state vector is assumed to be common knowledge to all firms, but $\epsilon_{imt}(a_{imt})$ is private information for firm *i*. For identification, we assume that after accounting for the actions of the other firms through argument a_{-imt}, the state variables of the other firms (s_{-imt}) do not affect directly firm *i*'s profits. This exclusion restriction will be used to identify the parameters of the deterministic

[21] The county level employment data were linked to our markets by calculating which county or counties each market is in. Since the FIRE employment variable describes the composition of employment in the are instead of counting employees, it is reasonable to apply these county-level data to our markets. When a market falls into more than one county, the data from the multiple counties is averaged, weighted by the market area falling into each.

part of the profit function in the two-step estimation. The final term, η, can be either private or common information, and includes all factors specific to the market, period, firm, or any combination of these that affect the profit of all alternatives equally. For example, η_{imt} can be a market-firm fixed effect η_{im} such as a firm's long-standing reputation in the area or a period fixed effect η_t stemming from the business cycle. The state variables include some factors, x_{imtj}, that vary across alternatives $j \in A$ and others, z_{imt}, that do not. The actions of the other firms enter observed profit through a set of competition variables $w_{imt}(a_{-imt})$. Observable profits are assumed to be linear in the state and competition variables:

$$\pi_{imt}(a_{imt}, a_{-imt}, s_{imt}; \theta) = \gamma_k' z_{imt} + \beta' x_{imtj} + \delta' w_{imt}(a_{-imt})$$

The firm does not observe the actions of other firms before choosing its action. Suppressing time and market subscripts, the firm's *expected* profit is

$$U_i(a_i, s_i; \theta) = E\pi_i(a_i, a_{-i}, s_i; \theta) + \epsilon_i(a_i) = \gamma_k' z_{imt} + \beta' x_{imtj} + \delta' E w_{imt}(a_{-imt})$$

where the expectation is taken over the space of other firms' private information. See Bajari et al. (2010) for a precise statement of this expectation. Informally, if it could observe the private information, firm *i* would know what each other firm would do. I.e., by assuming the other firms want to maximize profit, firm *i* can calculate the other firms' decision rules for quality choice that map their private information into their action space *A*. Taking expectation over the private information of the other firms yields an expected set of resulting competition variables, Ew_{imt}.

B. Estimation

We assume that $\epsilon_i(a_i)$ is drawn from the extreme value distribution as in the logit model. Then the firm chooses alternative $a_i = j$ such that $U_i(j, s_i; \theta) \geq U_i(k, s_i; \theta)$ for all $k \neq j$. Given the logit structure of the error terms, the probability that the firm chooses quality level *j* is thus

$$\Pr(a_{imt} = j|s_{imt}) = \frac{\exp\left(\gamma_k' z_{imt} + \beta' x_{imtj} + \delta_j{}'(Ew_{imt})\right)}{1 + \sum_k \exp\left(\gamma_k' z_{imt} + \beta' x_{imtj} + \delta_j{}'(Ew_{imt})\right)}$$

This formulation incorporates the usual identification assumption that the profit of base alternative 0, not entering, is normalized to zero. The expression above allows estimation of θ = (β,γ,δ) by maximum likelihood estimation (MLE) using a conditional logit model for choice of quality.[22] Note that the choice-invariant fixed effects η drop out of the conditional likelihood. For the same reason, the coefficients on z_{imt} must be alternative specific for the impact of the *z* to be estimable (as is familiar from the multinomial logit model).

The econometrician observes actual w_{imt} in the data, but not Ew_{imt}. We cannot substitute w_{imt} for Ew_{imt} in estimation, because the former is endogenous due to the simultaneity of the game. In the two-step method of Bajari et al. (2010), reduced form choice probabilities for competitors are estimated in the first step. By observing quality choices in a large number of markets, the econometrician forms a consistent estimate of the equilibrium choice probabilities. In our application, we use conditional logit in the first step, where the quality choices of each firm are regressed on z_{imt} and x_{imtj}, but not the competition variables. We then use the estimated choice probabilities to form the expected values of competition variables Ew_{imt} for the second-step estimation.

Since the state variables *x* and *z* are used to identify both the effects of (β,γ) and δ on the observed choices and profit is linear, an exclusion restriction avoids collinearity problems and helps identification. As mentioned above, the state variables specific to competitors are not included in the second-step estimation for the ILEC's decision. However, those excluded state variables are used to estimate the choice probabilities of competitors *k≠ i* in the first step, which then appear in the estimate of the expected action and consequence $Ew_{imt}(a_{-imt})$. In our application, the excluded instruments are

[22] Estimation was performed using the `asclogit` command in Stata 13.1.

infrastructure variables of the other firms, which we describe in the next subsection. Although these affect the actions of the other firms, conditional on those actions the infrastructure costs of the other firms should not affect directly the quality choice of firm *i*.

C. Specifics

For this version of the paper, we focus on ADSL provision by ILECs, the dominant telecommunications firms in the local markets. In California, this includes the "U-verse" DSL service offered by AT&T, as well as DSL service from Verizon and smaller providers. It does not the "FIOS" fiber-to-the-home service from Verizon, which instead counts as fiber-based broadband. The competitors include ADSL and fiber broadband from CLECs and cable modem broadband offerings.[23] For now, we set aside competition from less closely related offerings such as fixed or mobile wireless broadband, but recognize that these competitors may be more relevant in the future.

For estimation, the many speed categories in the NBM are collapsed into four alternatives for ADSL: greater or equal to 768kbps but less than 3 Mbps, 3Mbps to 6 Mbps, 6 Mbps to 10 Mbps, and 10 to 25 Mbps. No ILECs report offering ADSL with maximum speed below 768 kbps or greater than or equal to 25 Mbps during our time period. Choice $j = 0$ of not offering ADSL in the market gives the base alternative. These speed categories are also presented in Table 2 for reference. Variables z include demographic variables reflecting market characteristics and infrastructure variables. Variable *NearestAnySpeed* is the distance in miles (or log miles, in one of the estimations) to the Census block nearest to the center of market m where firm i offered broadband using the same technology (ADSL, for

[23] The distinction between ILECs and CLECs is clear within a market, because the NECA tariff identifies the locations of ILECs, and all other ADSL or fiber providers in that market must be CLECs. However, AT&T (and other large firms) may be treated as ILECs in some markets and CLECs in other markets if they do out-of-region entry.

the ILECs here) last period, per the NBM.[24] Thus, when the ILEC already offered ADSL in the market at *t*-1, *NearestAnySpeed* will be small. When the ILEC did not offer ADSL in the market the previous period but did in a nearby area, *NearestAnySpeed* will be smaller than if the firm offered ADSL in some distant location. Due to the presence of sunk costs in broadband infrastructure deployment, we thus expect that higher values of *NearestAnySpeed* will lower the probability of higher ADSL quality.

There are two *x* variables in the model: *NearestSameSpeed* and *SameSpeednotFound*. The former is constructed similarly to *NearestAnySpeed* but only ADSL in the same quality category counts in the calculations. Since this variable is missing when the firm did not offer a particular quality level anywhere in California the previous period, it is set to zero for such cases and an indicator variable *SameSpeednotFound* is set to one. *SameSpeednotFound* thus captures the impact of the variable *NearestSameSpeed* when the latter would logically be infinite. By logic similar to the above, we expect *NearestSameSpeed* and *SameSpeednotFound* for quality *j* both to impact negatively the probability of the firm offering quality *j*.[25]

The competition variables we choose are indicators for the presence of at least one competitor in a quality category. These are the *w* variables, which are functions of quality choice decision a_{-i} as introduced above. The indicators are cumulative, defined as $w_{imt}^{bj} = 1$ if broadband of type *b* and speed *j* or higher is offered in the market this period, with $w_{imt}^{bj} = 0$ otherwise. In the second-step estimations, Ew_{imt} are the expected values of these variables, where the w_{imt}^{bj} are arranged into a column vector including all *b* and *j*, and thus can take values between 0 and 1. For CLECs offering ADSL, there is an additional alternative *j* = 5 of greater or equal to 25 Mbps but less than 50 Mbps. For cable

[24] All distance variables were calculated based on the latitude and longitude of the central offices and Census block centroids. The great circle distance metric was computed and the nearest broadband locations for each firm and market were found using a FORTRAN program.

[25] Each *x* variable also has cross-impacts. For example, *NearestSameSpeed* for the highest quality level has a marginal effect on the probability of the firm offering ADSL in the lower quality categories. We calculate but do not report these cross-effects in the tables for the sake of brevity.

modem, the categories are j = 1 (less than 10 Mbps), 2 (10 Mbps to 25 Mbps), 3 (25 Mbps to 50 Mbps) 4 (50 Mbps to 100 Mbps), and 5 (100+ Mbps). For fiber, the quality categories are 0 (no entry or any fiber below 1 Gbps, grouped because there is little fiber below that speed) and 1 (gigabit fiber). These speed categories are also presented in Table 2 for reference.

Since the demographic variables are specific to the market and apply to all firms and periods, and because it is unrealistic to assume that two observations from different periods for the same firm and market are independent, we use standard errors that are robust to clustering within markets. Finally, even though we have panel data, in this version of the paper we do not exploit the panel structure of the data in estimation. All estimations use pooled data from the latest four periods, December 2011 to June 2013. Data from June 2011 is used only to calculate the lagged distance regressors for the first period included in the regression. We pool the data for several reasons. First, note that any market or market-firm fixed effect (η_m or η_{im} from above) that affects identically the profits of all quality levels is already accounted for in the conditional logit formulation. More practically, adding alternative-specific market fixed effects would add about four thousand coefficients to the model, making estimation difficult and possibly leading to incidental parameter bias. Finally, most of the variation in the data occurs in the cross section, not the time series within each market, and so fixed effect modeling would reduce greatly the effective size of the sample.

V. Results

The conditional logit estimations return a large number of estimated coefficients, since each regressor not varying over alternatives has a different coefficient for each of the four alternatives apart from the baseline choice. In our main estimation, we have 84 coefficients. While exponentiated coefficients from a conditional logit estimation have meaning as odds ratios relative to the base alternative, it is often more natural for econometricians and policy analysts to think in terms of marginal effects. The marginal effect of a regressor is the impact of a one unit increase in the regressor on the probability that the firm chooses a particular quality alternative. When the regressor is log(*x*), 0.01 times the marginal effect measures the impact of a 1% increase in *x*. Given our interest in the top end of the quality ladder, we show marginal impacts on the top three quality categories.[26] In the tables, we present the marginal effects at the median (*MEMdn*) and average marginal effects (*AME*) for the regressors of interest instead of the coefficients.[27] With MEMdn, the marginal effect is calculated once, setting all covariates at their median values. With AME, the marginal effect is calculated for each observation in the sample using actual values of regressors, with the results then averaged over the sample. The coefficients for our main estimation are included in the appendix for the interested reader.

A. First-step results

In the first step of estimation, the quality choices of competitors are regressed on the market demographics and the infrastructure variables used to proxy the costs of the firm. Since the first step is akin to a reduced form forecasting exercise, we err on the side of including a large set of predictors without regard for causal meaning of the coefficients, parsimony, or the significance of the estimates. The demographics include all those that are also included in the second step: market area in miles, population density and growth rate, median household income (averaged across Census block groups in the market) average age and age squared, average highest educational grade level achieved, the fraction of housing units that are rented or vacant, the fraction of the labor force working at home, the proportion of area employment that is in the financial, insurance, or real-estate (FIRE) sector, and the fraction of the market area that is under water. Where these variables are right skewed they are in logs, as noted in the tables. These variables were chosen based on a review of previous literature on the

[26] We focus on the top end, in addition, because few ADSL offerings by ILECs are in the 0 or 1 categories anyway.
[27] Another reason not to present the coefficients is that the marginal effects are functions of all the coefficients, and thus it is possible for the ME of a regressor to be statistically significant even when its coefficient is not. Thus checking for significance stars on coefficients can give a misleading sense of which regressors are truly important.

determinants of broadband entry decisions. An additional set of demographics are included only in the first-step estimations: the density of households in the market, the fractions of nonwhite people, the percentage female, the standard deviation of education attainment, and the proportion of workers with long commutes. These variables are not included in the second step because of concerns about near multicollinearity with other demographic variables or insignificance and for the sake of parsimony in presenting results.

While we do not present the results from the first step in tables here, we note two things. The infrastructure variables are clearly highly relevant. The coefficients for *NearestSameSpeed* and *SameSpeednotFound* are statistically significant at the 1% level for all competing broadband types. The coefficients for *NearestAnySpeed* and *AnySpeednotFound* (where the latter variable is defined similarly to *SameSpeednotFound* but across all speed categories > 0) are also generally (but not uniformly) highly significant. The high significance and impact of these infrastructure variables implies that they are likely to be effective instruments to identify separately the impact of the competition variables in the second-step estimation. We also note that some of the demographic variables have insignificant coefficients, even those that we would expect to have strong impacts on quality choice. While that does not mean that they have no significant marginal effect on choice probabilities (see footnote 27), it does mean that the infrastructure variables alone are capturing much of the variation in quality choice. The same first-step estimates of Ew_{imt} are used for all the second-step specifications.

B. Second-step results

1. Estimation 1: Demographics only

We begin with a simple specification for ILEC ADSL quality choice in which only demographic variables are included. Table 3 contains the marginal effects, MEMdn and AME. The marginal effects are expressed in percentage points. Here we focus mainly on the marginal effects for the highest speed

ADSL, contained in the rightmost set of columns. This speed, from 10 to 25 Mbps, ("high-speed ADSL" in the following discussion) is offered in California by ILECs held by 10 holding companies, the largest of which is AT&T offering its U-verse service.[28] Another four firms offer ADSL only with lower speeds.[29] The results show that several of the demographic variables significantly[30] increase the probability of offering high-speed ADSL: income, population density, age (at the 10% level only), rental housing %, and FIRE employment. One variable, the vacancy rate, significantly lowers the firm's probability of offering high-speed ADSL. For an example of interpreting the numbers, consider the income variable. The MEMdn for log income, 16.68, implies that an increase of market-area household income of 10% increases the probability of the ILEC offering high-speed ADSL by 1.67 percentage points. The AME for log income, 16.54, is similar in this case, although we observe that often the AME's are somewhat smaller than the MEMdn's.

2. Estimation 2: Add competition variables

Estimation 2 in Table 4 repeats the previous specification but with the competition variables included. In this estimation the infrastructure variables are still not included in the second step. Thus, the impacts of the competition variables may be biased due to endogeneity. For example, cost factors for firm *i* that are omitted in this regression, such as the presence of previously installed or nearby infrastructure, may be correlated with the quality choices of rivals through unobserved local factors. The estimates show apparently large impacts of competition on the ADSL quality choice. We consider

[28] The holding companies of these service providers are AT&T Inc., Calaveras Telephone Company, Frontier Communications Corporation, LICT Corporation, Ponderosa Communications, Inc., Sebastian Enterprises , Sierra Tel Communications Group, SureWest/Consolidated, Telephone and Data Systems, Inc., and Volcano Communications Company.

[29] The holding companies of these service providers are : Bryan Family Inc., Siskiyou Telephone Co., VARCOMM, Inc., and Verizon Communications. Verizon offers lower speed ADSL in some markets, but for higher qualities offers subscribers fiber (FIOS) instead.

[30] Here we mean "significant in either MEMdn or AME," and so below as well.

the impact of each type of competitor in turn. The marginal effect given for a speed category *j* is calculated to pertain to changing the competitors' maximum speed category from *j* – 1 to *j*.

The cable modem quality choice seems to affect the ILEC ADSL quality decisions a lot. When the cable modem service is relatively slow, the negative marginal effects for high-speed ADSL indicate that the ILECs are less likely to offer fast service themselves.[31] Once the cable companies move up into the DOCSIS 3.0 speed tiers, 50 Mbps and above, however, the ILEC is more likely to offer high-speed ADSL. The apparent effect of CLEC ADSL competition is similar: when the competitors' offerings are worse quality, the ILECs quality is less likely to be of the highest. The impact of CLEC gigabit fiber is small and insignificant. Given the omission of the infrastructure variables, we do not yet assign causal interpretation to these results. Comparing the results of the first two estimations, we see that the addition of the competition variables did not greatly change the marginal effects of the demographics. For this reason and to save space in the tables, we will not show the impacts of the demographic variables in the other tables below.

3. Estimation 3: The main specification, adding infrastructure variables

The addition of the infrastructure variables in the second-step estimation brings us to our preferred estimation (see Table 5). *SameSpeednotFound* and *NearestSameSpeed* have the expected negative impacts on same-choice alternatives. *NearestAnySpeed* has a further negative impact on the high-speed ADSL choice. After controlling for the same-speed infrastructure, the marginal effect for *NearestAnySpeed* can be interpreted as the impact of the distance to lower-speed infrastructure.

As expected from the discussion of the potential endogeneity problems in Estimation 2, the impacts of the competition variables, while qualitatively similar to before, have very different

[31] In this preliminary work, not all standard errors (s.e.'s) are available yet. Difficulties with numerical derivatives, and lack of time to program analytic derivatives yet, leads to the omitted SE's in this and following tables. Furthermore, as is common in the IO literature, the second-step s.e.'s do not account for estimation error in the first step. Thus our reported s.e.'s are smaller than those from the valid asymptotic variance-covariance matrix.

magnitudes in Estimation 3. The differing results show how the infrastructure variables help control for omitted variable bias. Since this is our main specification, we go through the results in greater detail here. When cable competitors switch from having no service to offering the slowest service (< 10 Mbps), the probability of high-speed ADSL rises by 12 percentage points. Looking at the columns in Table 5 for alternatives $j = 2$ and $j = 3$, we see that about two-thirds of these 12 percentage points come from upgrading from ADSL of speed between 3 and 6 Mbps, while about a quarter come from upgrading from ADSL of speed between 6 Mbps and 10 Mbps). Thus, whether an ILEC faces any cable competition at all appears to spur investment in ADSL speed. This impact (and those that follow) is not merely from the coincidence of DSL and cable modem service in more attractive markets, because the demographic regressors in the model control for the key market factors of income, population density, and so on. Furthermore, these apparent impacts are not merely reflections of favorable cost conditions for broadband provision, since last period's infrastructure variables account for that. Thus, they likely reflect the strategic considerations of ILECs in California and we interpret them as such.

However, as the cable competitors rise up the quality ladder, the impacts are not monotonic. When cable modem quality rises from between 10 and 25 Mbps to between 25 and 50 Mbps, the ILEC is 76 percentage points less likely to offer high-speed ADSL. Looking at the other columns of the table, we find that probability lost from alternatives 3 and 4 went to alternative 2. There are relatively few observations (88 out of 3,860 cases) with ILEC DSL entrants facing cable competition in speed category 3, and the large negative impact may merely be a small sample phenomenon, statistical significance notwithstanding. However, it may also be that the ILEC is responding with slower broadband to what the cable company did *not* do: upgrade to DOCSIS 3.0.[32] When the maximum speed of the cable

[32] The DOCSIS 2.0 standard can provide maximum usable throughput up to 38 Mbps downstream and up to 27 Mbps upstream. DOCSIS 3.0 can dramatically increase the capacity by a factor of the number of channels used (combined) in the network. Using DOCSIS 2.0 technology, ISPs can typically offer end-user downstream data rates

modem service rises to the two highest speed categories, the marginal effects on high-speed ADSL are positive. The largest marginal effects are for when the cable competitors upgrade from 25-50 Mbps (mostly DOCSIS 2.0) to 50-100 Mbps (DOCSIS 3.0). The MEMdn for high-speed ADSL is 88.3 percentage points, and the AME is 57.7. The probability gained comes mainly from alternative 2. In summary, ILECs generally respond to cable competition by upgrading their ADSL quality when they face any competition at all and when the quality of the competition becomes high.

In contrast with cable modem competition, there is no strongly significant evidence that ILECs pay much attention to the quality of their CLEC ADSL competition. The results are also in contrast to the previous estimation, in which CLEC ADSL had some highly significant marginal effects on high-speed ILEC ADSL. This difference shows the importance of the infrastructure variables in controlling for omitted variable bias. The largest impact on high-speed ILEC ADSL, 10 percentage points for the MEMdn and 8.8 for the AME, comes from when the CLECs move into the same speed category (between 10 and 25 Mbps). However, the MEMdn is not significant at the 5% level. The generally weak response to CLEC ADSL quality may indicate that ILECs do not perceive CLECs in California to be much of a competitive threat to their largely residential-oriented ADSL service. The largest CLEC ADSL provider, by far, is MegaPath (held by Platinum Equity, Inc.), which targets the business market.

Finally, the presence of gigabit CLEC fiber spurs a 6.2 percentage point increase (per MEMdn; 7.6 for AME) in high-speed ADSL. While Google fiber does not appear in our data, these results are in line with anecdotal accounts of incumbent broadband providers increasing their quality of service in response to Google fiber elsewhere in the country.[33]

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in the 10 to 25 Mbps range, whereas moving the downstream maximum data rates to the 50 to 100 Mbps range requires DOCSIS 3.0.

[33] For example, in the Austin area where Google Fiber is available, AT&T's U-verse DSL service has offered downstream speeds up to 300 Mbps. See http://www.fiercetelecom.com/story/att-begins-upgrading-austin-customers-1-gbps-service/2014-08-11 (accessed on 8/13/2014).

4. Additional estimations and robustness checks

Here we briefly consider three additional estimations performed as robustness checks. A subset of the results is in Table 6, where only the marginal effects for high-speed ADSL are shown. In Estimation 4, we use the log of the distances for the infrastructure variables instead of the level. The results are qualitatively similar to Estimation 3, except that the marginal effects of the slowest cable modem service and CLEC gigabit fiber lose significance. In Estimation 5, we replace the cable modem competition variables with their market-coverage-weighted counterparts. The results are very close to those of Estimation 3, even for the cable competition variables. Finally, we include all available demographics in Estimation 6. Again, the results are similar, except that the impact of CLEC gigabit fiber loses significance.

VI. Discussion and Conclusions

A. General

Our results show that ILECs respond to the quality choices of rival broadband providers. Their responses are heterogeneous to type of provider and to the level of quality. Specifically, ILECs appear to care more about rivals using cable modem or fiber technologies than rivals using a similar ADSL technology. The likely expectation for the ILEC is that if a consumer is going to switch services they are more likely to switch to a rival with a technology that can provide a very fast Internet service. Moreover, the level of speed matters in strategic responses. Particularly, when cable modem rivals move from no service to a “low” speed service tier or from a “medium” service tier to a “high” speed service tier, the ILEC also increases speed. This suggests strategic complementarity in the provision of quality and is consistent with the findings from Kugler and Weiss (2013) and Brueckner and Luo (2013) in the reaction-function literature as well as with Goolsbee and Petrin (2004), Savage and Wirth (2005) and Matsa (2011) in the reduced-form competition and quality literature.

Interestingly, however, when cable modem rivals move from “low” to “medium” speed service tiers, the ILEC is less likely to provide high quality ADSL, which suggests strategic substitutability in the provision of quality. This response may be due to changes in the price and quality elasticity of demands as suggested by theory. However, it is possible that this reflects the ILEC’s reaction to an underlying capacity constraint facing its rival, which does not have DOCSIS 3.0 installed. The result may even merely be an artifact of the data that will not persist once we expand our analysis. More empirical and theoretical analysis is required to fully understand this intriguing result. Overall, our empirical finding of a non-monotonic relationship between the quality choices of rival broadband providers also resembles the findings of Chen and Gayle (2013) from the airline industry.

B. Further work

The empirical results presented here are preliminary, and in this final section we discuss how we will refine them and which other questions we will address with the data. The next step in the project is to add additional competitors to the estimation of ILECs’ quality choice for ADSL. Besides the CLECs and cable modem providers, we have data on fixed and mobile wireless providers and other types of wireline providers (symmetric DSL, “other copper”, and so forth). In this initial work we focused only on the main competitors, but these other types of broadband may also affect the ILECs’ decisions. We also plan to explore the strategic quality choice of other broadband players besides ILECs offering ADSL. That is, even those we model the CLEC and cable modem providers in the first step of estimation, we have not yet included them in the second step. It may also be interesting to use the count of competitors in each quality category instead of merely an indicator for at least one competitors’ presence there. This is not likely to be important for cable companies, since overbuilding is rare in California. However, it may be more important for CLEC competition. We also have not yet re-estimated the model using the alternative 18 kf market definition, which we can use as a further robustness check.

Once we have a more mature set of estimation results in hand, we plan to exploit the model to address important questions of public policy. For example, our results so far suggest that intermodal competition is much more important than intramodal competition among ILECs and CLECs. If this result persists as we refine our results, it may indicate that unbundling policies aimed at the local loop would be largely ineffective at increasing the quality of service offerings to residents. Our model will allow us to address this question quantitatively. As a second example, we will also be able to address the impact of a merger between cable companies or fiber broadband providers on the quality offered by those firms and their competitors in the market. Such analyses will be useful for purposes of merger review.

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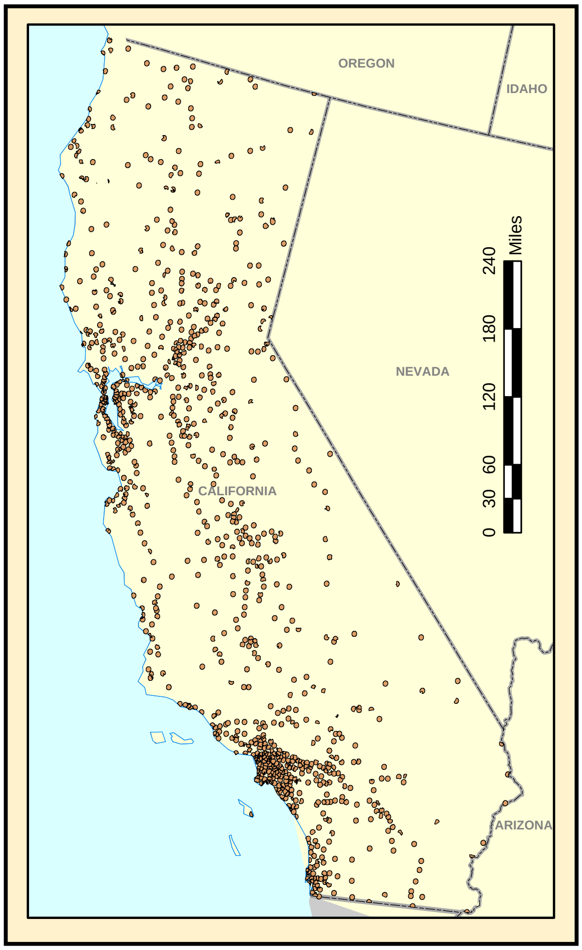
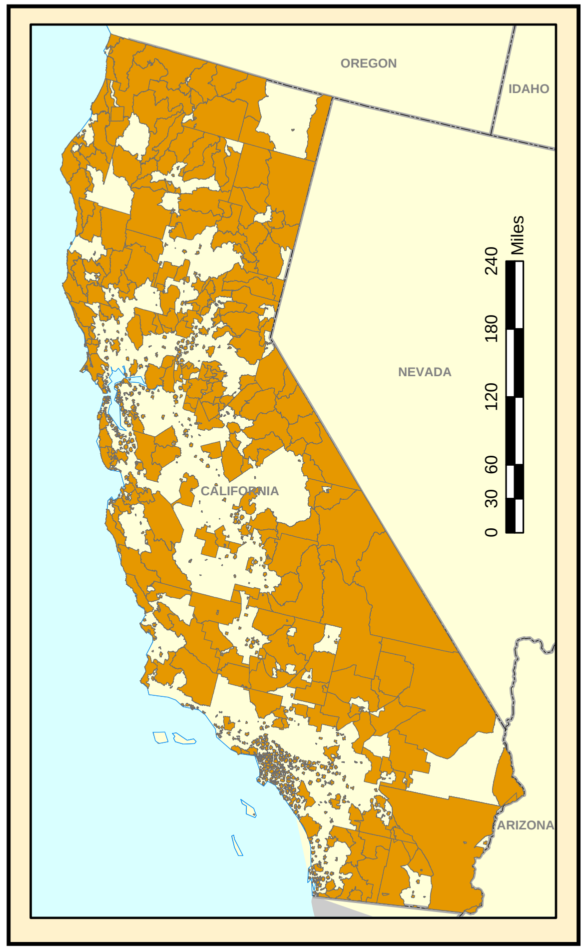
Figure 1: The Market Areas in California



Step-Two Market Areas



Step-Three Market Areas

Figure 2: Example of Urban Market Areas: Los Angeles Area

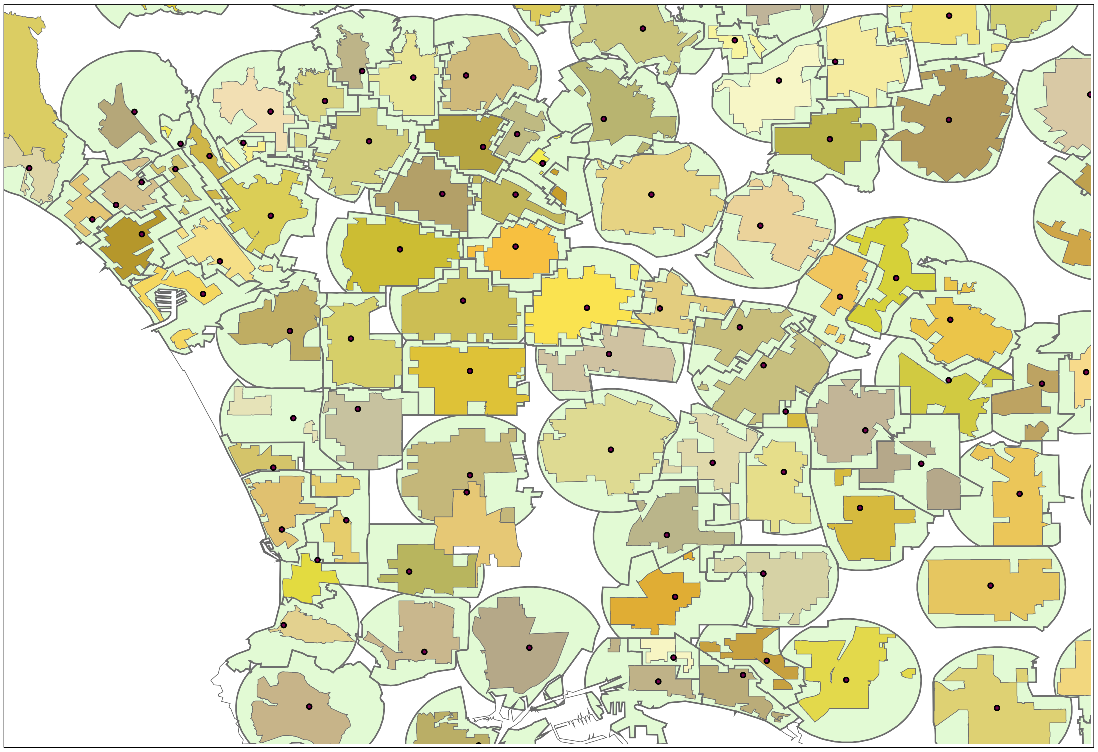


Figure 3: Example of Rural Market Areas: Rural Fresno County

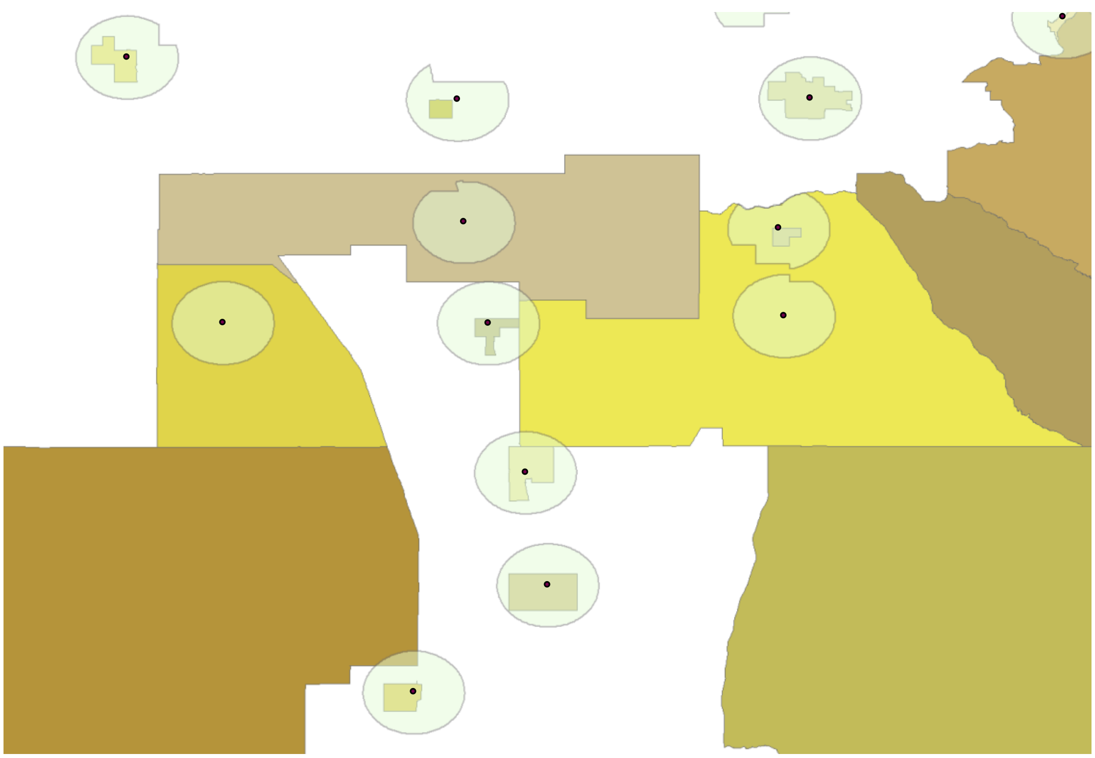


Figure 4: ILEC ADSL Quality Choice in California

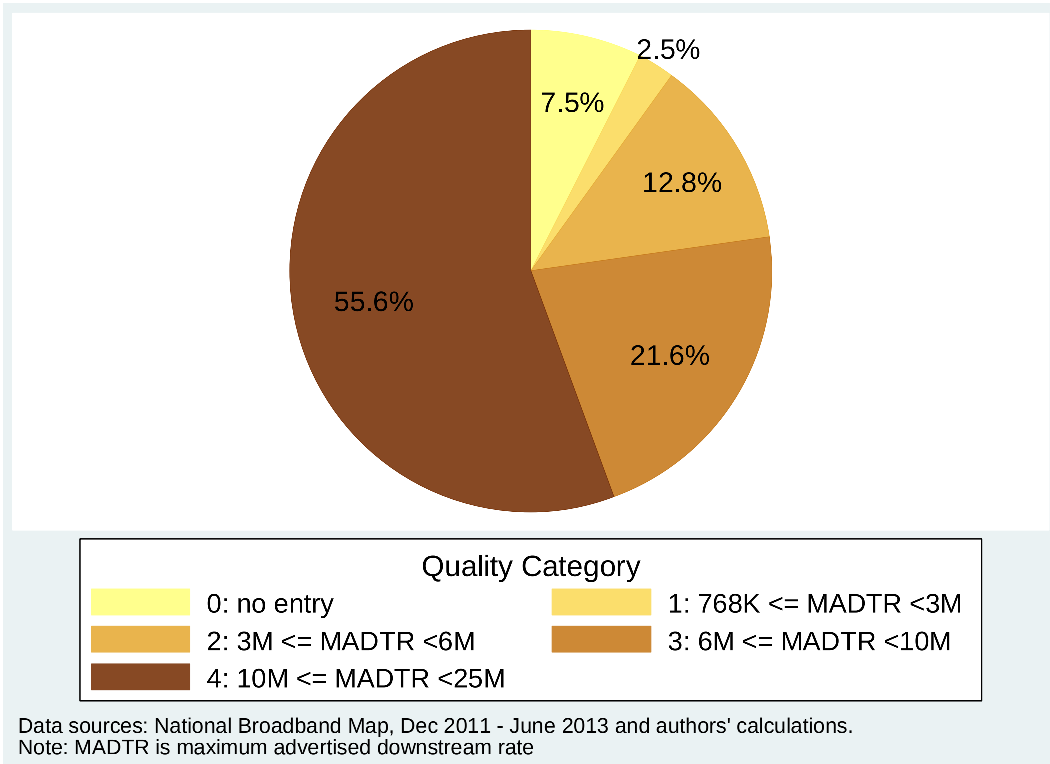


Table 1: Summary Statistics

	Mean	s.d.	Min	Max
Y (chosen alternatives)	3.154	1.197	0	4
Competition variables†				
Cable modem service				
CM <10 M	0.853	0.355	0	1
10M < CM < 25M	0.826	0.379	0	1
25M < CM < 50M	0.761	0.427	0	1
50M < CM <100 M	0.738	0.440	0	1
100M < CM	0.471	0.499	0	1
CLEC ADSL				
768K < CLEC ADSL <3M	0.634	0.482	0	1
3M < CLEC ADSL <6M	0.509	0.500	0	1
6M < CLEC ADSL <10M	0.458	0.498	0	1
10M < CLEC ADSL <25M	0.384	0.486	0	1
25M < CLEC ADSL <50M	0.109	0.312	0	1
CLEC fiber > 1G	0.223	0.417	0	1
Main Demographics				
Area (log mi)	2.473	0.460	-1.150	2.986
Pop. density (log)	6.479	3.082	-2.387	11.327
Pop. growth	0.110	0.801	-0.916	22.752
Age	37.854	6.136	20.093	62.661
Education (grade)	13.694	1.690	7.895	17.445
Rental housing (%)	0.413	0.177	0.010	1.000
Work at home	0.204	0.070	0.000	0.638
Water area (%)	0.013	0.035	0.000	0.493
Income (log)	11.090	0.399	9.322	12.544
Vacancy rate (log)	-2.339	0.786	-4.615	-0.109
FIRE employment (log %)	-2.831	0.272	-3.597	-2.054
Additional Demographics				
HH density (log)	5.424	3.044	-3.294	10.205
Nonwhite %	0.270	0.174	0.000	0.884
Female %	0.493	0.051	0.038	0.631
Education, s.d.	514.379	342.021	63.649	2262.061
Long commute %	0.199	0.106	0.000	0.868

†The competition variables are defined to represent all possible speeds that competitors could offer in the market. When the maximum speed in the NBM of competitors is in a particular category, then the indicator variables equal 1 for that and lower speed categories.

Table 2: Quality Alternatives – The Downstream Speed Categories

Alternative	Speed Category		
	ILEC ADSL	**CLEC ADSL**	**Cable Modem**
0	No entry	No entry	No entry
1	768K ≤ MADTR <3M	768K ≤ MADTR <3M	MADTR <10 M
2	3M ≤ MADTR <6M	3M ≤ MADTR <6M	10M ≤ MADTR < 25M
3	6M ≤ MADTR <10M	6M ≤ MADTR <10M	25M ≤ MADTR < 50M
4	10M ≤ MADTR <25M	10M ≤ MADTR <25M	50M ≤ MADTR < 100M
5	NA	25M ≤ MADTR <50M	100M ≤ MADTR

Table notes: *MADTR* is the maximum advertised downstream transmission rate.

Table 3: ILEC ADSL Estimation 1 – Demographics only

	Prob(3M < ADSL speed <6M)				Prob(6M < ADSL speed <10M)				Prob(10M < ADSL speed <25M)			
	ME at median		Average ME		ME at median		Average ME		ME at median		Average ME	
	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE
Demographics												
Area (log mi)	-1.022	1.953	-1.294	2.037	-9.903***	3.238	-8.533***	3.044	9.883**	3.897	7.194*	3.674
Pop. density (log)	-0.447	0.435	0.145	0.443	0.937	0.815	1.551**	0.643	0.284	0.821	1.355**	0.635
Pop. growth	0.600	1.100	0.470	1.190	-7.035	4.691	-6.111	4.022	6.104	4.086	4.408	3.001
Age	-1.645	1.046	-1.475	1.101	-1.498	2.023	-0.921	1.753	3.246	2.045	3.015*	1.711
Age squared	0.021*	0.012	0.019	0.013	0.008	0.025	0.003	0.021	-0.029	0.025	-0.028	0.021
Education (grade)	-0.068	0.751	0.110	0.768	1.475	1.358	1.464	1.160	-1.142	1.349	-0.549	1.136
Rental housing (%)	-14.497**	7.313	-13.237*	7.016	-37.210***	12.456	-28.700***	10.136	53.210***	12.739	45.438***	10.415
Work at home	-8.695	11.971	-10.910	12.095	-31.780	22.402	-28.841	18.529	37.473	23.134	26.151	19.458
Water area (%)	32.732*	17.782	39.309**	18.081	-87.169*	48.996	-67.503	41.034	61.927	44.643	55.993	35.660
Income (log)	-6.483*	3.761	-4.939	3.656	-8.468	6.624	-4.726	5.486	16.684**	6.867	16.539***	5.747
Vacancy rate (log)	2.466	1.841	2.258	1.790	10.395***	3.244	8.296***	2.622	-12.939***	3.247	-10.712***	2.682
FIRE employment (log %)	-5.347*	2.828	-4.563	2.774	-22.731***	6.094	-17.710***	4.899	28.384***	6.190	24.037***	4.945

*10% sig level ** 5% sig level ***1% sig level.

Table notes: Estimation method is Conditional Logit. Since there are no competition variables, the two step estimation described in the text (refer to section IV.B in the text) is not required in this specification. SE's are robust to clustering on markets. "ME at median" is the marginal effect of a one unit increase in the regressor in the row label on the choice probability given in the column superheading, calculated at the median values of all regressors. "Average ME" is the marginal effect of a one unit increase in the regressor in the row label on the choice probability given in the column superheading, calculated at actual regressor values and averaged over the sample. Choice alternatives not shown in the table but included in the estimation are 1) no ADSL broadband, and 2) Prob(768K < ADSL speed <3M).

Table 4: ILEC ADSL Estimation 2 – Competition variables and demographics

	Alternative 2 Prob(3M < ADSL speed <6M)				Alternative 3 Prob(6M < ADSL speed <10M)				Alternative 4 Prob(10M < ADSL speed <25M)			
	MEMdn		AME		MEMdn		AME		MEMdn		AME	
	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE
Competition variables†												
CM <10 M	-9.846	7.332	-5.055		39.410***	14.640	32.850		-26.950**	12.110	-19.072	
10M < CM < 25M	43.690***	12.730	33.305		-31.520**	15.870	-22.652		-11.910	11.700	-12.425	
25M < CM < 50M	40.230***	11.610	43.626		-28.470***	10.240	-27.666		-11.770*	6.197	-15.258	
50M < CM <100 M	-76.51***	5.089	-71.584		31.460***	5.296	29.042		45.820***	5.658	46.794	
100M < CM	-11.15***	3.926	-8.644		-9.640*	4.925	-8.585		20.520***	4.956	15.782	
768K < CLEC ADSL <3M	1.388	5.856	3.524		-2.155	6.883	0.319		2.129	7.114	5.269	
3M < CLEC ADSL <6M	-5.243	6.984	-5.304		2.416	14.730	1.387		2.220	14.070	0.391	
6M < CLEC ADSL <10M	-8.570	5.639	-8.353		40.230***	15.550	26.689		-33.750**	14.270	-30.193	
10M < CLEC ADSL <25M	0.869	2.938	0.225		-23.050***	8.682	-17.865		22.030***	7.460	17.120	
25M < CLEC ADSL <50M	-1.176	3.037	-0.088		-39.920***	5.804	-28.432		42.920***	5.925	34.986	
CLEC fiber > 1G	-13.11***	3.540	-9.706		11.280	8.536	12.109		2.555	8.439	8.028	
Demographics												
Area (log mi)	-2.676	2.545	-1.680	1.821	-7.311**	3.703	-4.717*	2.697	10.048**	4.471	7.659**	3.446
Pop. density (log)	0.116	0.664	0.598	0.467	1.061	0.950	1.344**	0.638	-0.971	0.908	0.205	0.627
Pop. growth	2.463	2.027	1.299	1.515	-13.576**	5.813	-9.899**	4.128	10.956**	4.957	7.180**	3.140
Age	-0.010	1.581	-0.020	1.114	-2.889	2.288	-1.975	1.709	2.875	2.272	2.051	1.673
Age squared	0.005	0.018	0.004	0.013	0.025	0.027	0.017	0.020	-0.030	0.027	-0.020	0.020
Education (grade)	-0.286	1.048	0.067	0.753	0.617	1.689	0.740	1.225	-0.218	1.632	0.321	1.185
Rental housing (%)	3.607	9.950	2.297	7.010	-53.267***	15.314	-37.238***	10.400	49.788***	14.795	35.859***	10.390
Work at home	-7.971	15.331	-8.766	11.236	-37.606	24.265	-29.685*	16.733	44.447*	23.856	26.861	17.726
Water area (%)	38.599*	23.005	35.697**	16.719	-83.318	52.120	-48.197	35.932	48.603	45.621	50.388	32.816
Income (log)	3.346	4.424	2.934	3.183	-5.649	8.181	-3.133	5.828	2.465	7.845	2.732	5.728

Table continued next page

	Alternative 2 Prob(3M < ADSL speed <6M)				Alternative 3 Prob(6M < ADSL speed <10M)				Alternative 4 Prob(10M < ADSL speed <25M)			
	MEMdn		AME		MEMdn		AME		MEMdn		AME	
	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE	Est.	SE
Vacancy rate (log)	-0.668	2.302	-0.650	1.612	13.733***	3.784	9.300***	2.498	-13.188***	3.554	-9.925***	2.491
FIRE employment (log %)	-0.588	4.511	-0.284	3.168	-38.049***	8.272	-26.087***	5.267	38.768***	7.835	28.438***	5.356

*10% sig level ** 5% sig level ***1% sig level.

†For the competition variables, the marginal effect is for moving from the speed category below to the category in the row label. E.g., for the row labeled “10M < CM < 25M” the ME is for moving from facing CM competitors with a max speed of less than 10M (“CM <10 M”) to facing CM competitors with a max speed of between 10M and 25M.

Table notes: Estimates are from the second step, and all the regressors labeled “competition variables” are the expected values calculated from the first step (refer to section IV.B in the text). See also notes to previous table.

Table 5: ILEC ADSL Estimation 3 (Main estimation) – Demographics, Competition variables, and Nearest Infrastructure variables

	Alternative 2			Alternative 3			Alternative 4		
	Prob(3M < ADSL speed <6M)			Prob(6M < ADSL speed <10M)			Prob(10M < ADSL speed <25M)		
	MEMdn		AME	MEMdn		AME	MEMdn		AME
	Est.	SE	Est.	Est.	SE	Est.	Est.	SE	Est.
Competition variables									
CM <10 M	-8.215***	2.050	-14.204	-2.950	5.733	9.159	12.190**	6.210	13.605
10M < CM < 25M	11.000*	6.371	17.335	5.262	8.081	-7.888	-16.960	11.820	-15.807
25M < CM < 50M	88.550***	6.431	77.247	-11.400*	6.359	-18.942	-76.460***	10.870	-46.781
50M < CM <100 M	-96.230***	1.008	-84.814	7.890***	1.793	22.649	88.310***	2.359	56.720
100M < CM	-1.865**	0.906	-3.333	-2.413	1.645	0.029	4.285**	2.160	3.874
768K < CLEC ADSL <3M	-2.262	1.529	-0.276	-2.829	2.837	0.784	5.422*	3.277	5.784
3M < CLEC ADSL <6M	-0.466	1.777	-1.912	-0.822	3.334	-1.535	1.198	3.803	0.234
6M < CLEC ADSL <10M	-1.228	1.681	-8.962	10.180*	5.387	9.726	-9.436	6.110	-6.464
10M < CLEC ADSL <25M	-0.629	0.789	1.546	-8.855*	4.568	-3.453	10.030*	5.207	8.767
25M < CLEC ADSL <50M	3.318**	1.571	12.446	-5.660***	1.485	-22.302	1.310	2.409	-3.930
CLEC fiber > 1G	-3.101***	0.822	-9.931	-3.069*	1.774	3.048	6.212***	2.033	7.570
Demographics									
Included but not shown									
Cost/Infrastructure									
SameSpeednotFound (own effect)	-3.142***	0.657	NA	-7.237***	1.293	NA	-88.510***	1.586	NA
NearestSameSpeed (log mi, own effect)	-0.100***	0.018	NA	-0.221***	0.043	NA	-0.307***	0.048	NA
NearestAnySpeed (log mi)	0.313**	0.152	0.324	0.527	0.321	0.036	-0.853*	0.436	-0.785

*10% sig level ** 5% sig level ***1% sig level.

Table notes: Estimates are from the second step. See also notes to previous table.

Table 6: Additional ILEC ADSL Estimations (Robustness Checks) – Results for the Choice of High Speed ILEC ADSL, Prob(10M < ADSL speed <25M)

	Estimation 4 Log distance variables			Estimation 5 CM coverage-adjusted			Estimation 6 Expanded set of demographics		
	MEMdn		AME	MEMdn		AME	MEMdn		AME
	Est.	SE	Est.	Est.	SE	Est.	Est.	SE	Est.
Competition variables									
CM <10 M	4.910	3.128	11.231	11.000**	5.141	13.161	11.740*	7.002	12.096
10M < CM < 25M	-4.850	5.424	-9.504	-19.310	12.740	-17.818	-20.680	13.420	-16.731
25M < CM < 50M	-91.610***	5.722	-46.370	-75.860***	12.170	-46.378	-72.210***	12.130	-45.683
50M < CM <100 M	91.710***	2.702	47.058	88.880***	2.330	56.697	86.870***	2.676	56.384
100M < CM	4.659***	1.788	7.546	3.925*	2.183	3.722	4.810**	2.446	4.166
768K < CLEC ADSL <3M	1.081	2.527	3.047	6.265*	3.276	6.507	1.618	3.382	2.540
3M < CLEC ADSL <6M	2.997	2.431	-0.033	1.524	3.820	0.337	1.257	4.400	-0.084
6M < CLEC ADSL <10M	-5.894	3.731	-3.093	-9.273	6.161	-6.138	-7.285	6.234	-3.641
10M < CLEC ADSL <25M	2.784	3.559	0.996	9.293*	5.228	7.787	6.009	5.192	4.600
25M < CLEC ADSL <50M	-0.760	3.418	-4.793	1.613	2.502	-2.887	2.285	3.955	-3.664
CLEC fiber > 1G	0.475	2.050	3.022	6.791***	2.028	8.025	2.673	2.916	2.594
Demographics									
Included but not shown									
Cost/Infrastructure									
SameSpeednotFound†	-90.240***	1.541		-88.310***	1.605		-87.410***	1.811	
NearestSameSpeed (log mi)†	-4.660***	0.860		-0.313***	0.047		-0.330***	0.054	
NearestAnySpeed (log mi)	-2.366***	0.553	-4.071	-0.886**	0.448	-0.798	-0.924*	0.487	-0.777

*10% sig level ** 5% sig level ***1% sig level. †Own effect (effect on alternative 4, in this case).

Table Notes: Each set of three columns pertains to a different estimation specification. 1st: distances in the infrastructure variables are in logs instead of levels. 2nd: cable modem competition variables are weighted by fraction of market covered by the cable service area. 3rd: all available demographics are included.

Appendix: Raw Estimation Output for Estimation 3 (Main Specification)

This appendix contains the estimated coefficients for Estimation 3, our preferred specification. These are the coefficients underlying the marginal effects reported in Table 5.

```
Alternative-specific conditional logit         Number of obs      =     19280
Case variable: caseID                          Number of cases    =      3856

Alternative variable: sbin_option              Alts per case: min =         5
                                                              max =         5

                                                  Wald chi2(98)    =   1097.19
Log pseudolikelihood = -2032.1477                 Prob > chi2      =    0.0000

                                       (Std. Err. adjusted for 965 clusters in market)
--------------------------------------------------------------------------------------
                     |               Robust
              choice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------------+----------------------------------------------------------------
sbin_option          |
      SameBBnotFound |  -6.705426   .3666517   -18.29   0.000     -7.42405   -5.986802
nearestSameBBifFound |  -.0328376   .0046148    -7.12   0.000    -.0418824   -.0237928
---------------------+----------------------------------------------------------------
0                    |  (base alternative)
---------------------+----------------------------------------------------------------
1                    |
   nearestSameTechBB |   -.151646   .0288382    -5.26   0.000    -.2081678   -.0951243
Expected_CM_Quality1 |  -1.606585   2.428441    -0.66   0.508    -6.366242    3.153072
Expected_CM_Quality2 |  -2.245731   3.062607    -0.73   0.463     -8.24833    3.756869
Expected_CM_Quality3 |   9.618941   4.032032     2.39   0.017     1.716304    17.52158
Expected_CM_Quality4 |  -7.919902   3.662783    -2.16   0.031    -15.09882   -.7409792
Expected_CM_Quality5 |   2.729569   1.313439     2.08   0.038     .1552752    5.303863
 Exp_ADSL_CLEC_Qlty1 |  -2.027241   2.627857    -0.77   0.440    -7.177747    3.123265
 Exp_ADSL_CLEC_Qlty2 |   2.740354   3.469344     0.79   0.430    -4.059436    9.540143
 Exp_ADSL_CLEC_Qlty3 |  -3.455721   2.373179    -1.46   0.145    -8.107067    1.195625
 Exp_ADSL_CLEC_Qlty4 |   .9968364   1.936998     0.51   0.607    -2.799611    4.793284
 Exp_ADSL_CLEC_Qlty5 |  -1.028206    1.74516    -0.59   0.556    -4.448657    2.392245
Exp_Fiber_CLEC_Qlty5 |   .7254898   1.618034     0.45   0.654    -2.445799    3.896779
              areaLn |   .4020212   .8366828     0.48   0.631    -1.237847    2.041889
            popDenLn |  -.2090502   .1254246    -1.67   0.096    -.4548779    .0367775
           PopGrowth |   .1483223   .2739474     0.54   0.588    -.3886047    .6852494
        AGE_MEAN_mkt |   .1743126   .3205165     0.54   0.587    -.4538882    .8025135
               ageSq |  -.0013766   .0038701    -0.36   0.722    -.0089618    .0062086
       EDUC_MEAN_mkt |   .0205232   .2514362     0.08   0.935    -.4722827    .5133291
           _RENT_mkt |   2.682896   1.404381     1.91   0.056    -.0696403    5.435432
       _WORKHOME_mkt |  -3.276944   2.775446    -1.18   0.238    -8.716719    2.162831
     _WATERSHARE_mkt |   -9.33643   6.036809    -1.55   0.122    -21.16836    2.495499
            incomeLn |   .5662495   .9756816     0.58   0.562    -1.346051     2.47855
       VacancyRateLn |   -.800186    .506348    -1.58   0.114     -1.79261    .1922379
           FIREempLn |   .4413859   1.268756     0.35   0.728    -2.045329    2.928101
               _cons |  -16.23696   12.83698    -1.26   0.206    -41.39698    8.923071
---------------------+----------------------------------------------------------------
```

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choice	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
2						
nearestSameTechBB	-.1777229	.034506	-5.15	0.000	-.2453534	-.1100924
Expected_CM_Quality1	-.6136592	1.65967	-0.37	0.712	-3.866552	2.639233
Expected_CM_Quality2	-.0345336	2.058637	-0.02	0.987	-4.069388	4.000321
Expected_CM_Quality3	12.14041	3.565601	3.40	0.001	5.151961	19.12886
Expected_CM_Quality4	-10.58655	3.076683	-3.44	0.001	-16.61674	-4.556366
Expected_CM_Quality5	.9277611	1.016057	0.91	0.361	-1.063673	2.919195
Exp_ADSL_CLEC_Qlty1	2.081478	2.114908	0.98	0.325	-2.063665	6.226621
Exp_ADSL_CLEC_Qlty2	-.9551984	2.949447	-0.32	0.746	-6.736008	4.825611
Exp_ADSL_CLEC_Qlty3	-4.057481	1.793257	-2.26	0.024	-7.5722	-.5427621
Exp_ADSL_CLEC_Qlty4	2.644875	1.280144	2.07	0.039	.1358395	5.153911
Exp_ADSL_CLEC_Qlty5	-2.278049	1.234551	-1.85	0.065	-4.697726	.141627
Exp_Fiber_CLEC_Qlty5	-.5608268	1.394808	-0.40	0.688	-3.294601	2.172947
areaLn	-.3420503	.3312069	-1.03	0.302	-.9912039	.3071034
popDenLn	-.0072046	.1163476	-0.06	0.951	-.2352417	.2208326
PopGrowth	-.0147865	.2916122	-0.05	0.960	-.5863359	.5567628
AGE_MEAN_mkt	-.0682873	.2935228	-0.23	0.816	-.6435815	.5070069
ageSq	.0019221	.0035754	0.54	0.591	-.0050854	.0089297
EDUC_MEAN_mkt	.0196186	.2104462	0.09	0.926	-.3928485	.4320857
_RENT_mkt	2.93263	1.384258	2.12	0.034	.2195339	5.645726
_WORKHOME_mkt	-7.095614	2.684007	-2.64	0.008	-12.35617	-1.835057
_WATERSHARE_mkt	.0487735	3.898462	0.01	0.990	-7.592071	7.689618
incomeLn	.3991842	.8799402	0.45	0.650	-1.325467	2.123835
VacancyRateLn	-.8423771	.4424499	-1.90	0.057	-1.709563	.0248087
FIREempLn	-.1848963	1.321602	-0.14	0.889	-2.775189	2.405396
_cons	-9.969011	12.57489	-0.79	0.428	-34.61535	14.67733
3						
nearestSameTechBB	-.2045352	.0440739	-4.64	0.000	-.2909184	-.118152
Expected_CM_Quality1	2.321899	1.937166	1.20	0.231	-1.474877	6.118674
Expected_CM_Quality2	-3.027535	2.354243	-1.29	0.198	-7.641767	1.586697
Expected_CM_Quality3	4.398966	3.874984	1.14	0.256	-3.195863	11.9938
Expected_CM_Quality4	-2.075728	3.355484	-0.62	0.536	-8.652355	4.500899
Expected_CM_Quality5	1.28571	.9971871	1.29	0.197	-.6687413	3.24016
Exp_ADSL_CLEC_Qlty1	2.199401	2.133433	1.03	0.303	-1.98205	6.380853
Exp_ADSL_CLEC_Qlty2	-.9590137	3.004932	-0.32	0.750	-6.848571	4.930544
Exp_ADSL_CLEC_Qlty3	-2.363884	1.820055	-1.30	0.194	-5.931126	1.203358
Exp_ADSL_CLEC_Qlty4	2.252075	1.213814	1.86	0.064	-.1269563	4.631106
Exp_ADSL_CLEC_Qlty5	-6.185145	1.499646	-4.12	0.000	-9.124397	-3.245893
Exp_Fiber_CLEC_Qlty5	.8785445	1.321831	0.66	0.506	-1.712197	3.469286
areaLn	-.2591963	.3543046	-0.73	0.464	-.9536205	.4352279
popDenLn	-.064573	.1167247	-0.55	0.580	-.2933492	.1642031
PopGrowth	-.5781168	.4325214	-1.34	0.181	-1.425843	.2696096
AGE_MEAN_mkt	-.0641535	.3035055	-0.21	0.833	-.6590132	.5307063
ageSq	.0014001	.0037028	0.38	0.705	-.0058573	.0086574
EDUC_MEAN_mkt	-.0032367	.211315	-0.02	0.988	-.4174065	.4109331
_RENT_mkt	2.017749	1.3496	1.50	0.135	-.6274183	4.662917
_WORKHOME_mkt	-7.445426	2.614233	-2.85	0.004	-12.56923	-2.321623
_WATERSHARE_mkt	-7.152064	4.262157	-1.68	0.093	-15.50574	1.20161
incomeLn	.000525	.9197481	0.00	1.000	-1.802148	1.803198
VacancyRateLn	-.4264742	.441726	-0.97	0.334	-1.292241	.4392929
FIREempLn	-1.007138	1.282111	-0.79	0.432	-3.520029	1.505753
_cons	-5.700624	12.97699	-0.44	0.660	-31.13506	19.73381

Table continued next page

Table continued from previous page

choice	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
4						
nearestSameTechBB	-.2867449	.0608138	-4.72	0.000	-.4059378	-.1675519
Expected_CM_Quality1	2.851677	1.937474	1.47	0.141	-.9457034	6.649057
Expected_CM_Quality2	-3.843347	2.273202	-1.69	0.091	-8.298741	.6120472
Expected_CM_Quality3	2.877306	3.894042	0.74	0.460	-4.754875	10.50949
Expected_CM_Quality4	-.0436249	3.416056	-0.01	0.990	-6.738971	6.651721
Expected_CM_Quality5	1.695662	1.020376	1.66	0.097	-.3042389	3.695563
Exp_ADSL_CLEC_Qlty1	2.663995	2.117224	1.26	0.208	-1.485688	6.813678
Exp_ADSL_CLEC_Qlty2	-.790212	2.956526	-0.27	0.789	-6.584896	5.004472
Exp_ADSL_CLEC_Qlty3	-3.599671	1.830709	-1.97	0.049	-7.187794	-.0115469
Exp_ADSL_CLEC_Qlty4	3.253188	1.304257	2.49	0.013	.6968909	5.809485
Exp_ADSL_CLEC_Qlty5	-3.738563	1.179449	-3.17	0.002	-6.050241	-1.426886
Exp_Fiber_CLEC_Qlty5	1.472453	1.333173	1.10	0.269	-1.140519	4.085425
areaLn	-.5987834	.3615515	-1.66	0.098	-1.307411	.1098446
popDenLn	.0207623	.1183542	0.18	0.861	-.2112078	.2527323
PopGrowth	-.1246738	.2665312	-0.47	0.640	-.6470652	.3977177
AGE_MEAN_mkt	-.2474044	.2990171	-0.83	0.408	-.8334671	.3386584
ageSq	.0034348	.0036747	0.93	0.350	-.0037675	.010637
EDUC_MEAN_mkt	.1461308	.2129376	0.69	0.493	-.2712192	.5634807
_RENT_mkt	1.394047	1.3606	1.02	0.306	-1.27268	4.060774
_WORKHOME_mkt	-7.182032	2.861303	-2.51	0.012	-12.79008	-1.573982
_WATERSHARE_mkt	-2.34731	3.944568	-0.60	0.552	-10.07852	5.383902
incomeLn	-.3398597	.9353834	-0.36	0.716	-2.173178	1.493458
VacancyRateLn	-.9037069	.432946	-2.09	0.037	-1.752265	-.0551484
FIREempLn	-.7777628	1.265103	-0.61	0.539	-3.257319	1.701793
_cons	1.772227	13.04927	0.14	0.892	-23.80388	27.34833