Entry Threat, Entry Delay, and Internet Speed: The Timing of the U.S. Broadband Rollout*

Kyle Wilson[1], Mo Xiao[2], and Peter F. Orazem[3]

[1]Pomona College

[2]University of Arizona

[3]Iowa State University

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Abstract

In a rapidly growing industry, potential entrants strategically choose which local markets to enter. Facing the threat of additional entrants, a potential entrant may lower its expectation of future profits and delay entry into a local market, or it may accelerate entry due to preemptive motives. Using the evolution of local market structures of broadband Internet service providers from 1999 to 2007, we find that the former effect dominates the latter after allowing for spatial correlation across markets and accounting for endogenenous market structure. On average, it takes 3 years longer for threatened markets to receive their first broadband entrant. Moreover, this entry delay has long-run negative implications for the divergence of the U.S. broadband infrastructure: one year of entry delay translates into an 11% decrease in average present-day download speeds.

Keywords: Entry, Entry Threat, Endogenous Market Structure, Internet Service Providers, Internet Speed

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*Kyle Wilson: Department of Economics, Pomona College, Claremont, CA 91711, kyle.wilson@pomona.edu; Mo Xiao, Department of Economics, University of Arizona, Tucson, AZ 85721, mxiao@eller.arizona.edu; Peter F. Orazem, Department of Economics, Iowa State University, Ames, IA 50011, pfo@iastate.edu. We thank Dan Ackerberg, Ashley Langer, Gautam Gowrisankaran, Miguel Villas-Boas, and participants of various seminars and conferences. Mo Xiao thanks the NET Institute (www.NETinst.org) and the Eller College small research grant for financial support. All errors are ours.

1 Introduction

The U.S. broadband industry has been plagued by the problem of "digital divide." The Federal Communications Commission (FCC) reported in 2015 that 53% of rural Americans but only 8% of urban Americans lack access to broadband. This inequality is often attributed to socio-economic differences in populations and cost differences across terrains. The uneven deployment of internet infrastructure, however, is ultimately determined by market forces. Since the advent of the industry, highly strategic Internet Service providers (ISPs) have sought to optimally locate and expand while responding to their rivals' attempts to do the same, and these interactions have given rise to the competitive landscape we face today.

We examine the early U.S. broadband industry and its aftermath under the lens of Douglass North's "path dependence." In the early 2000s, the internet industry is in its infancy. Potential entrants, whether they are telecommunications veterans or new start-ups, roll out their network gradually and strategically. Looking for the next hot spot to enter, a potential entrant must anticipate the actions of potential rivals in the marketplace. A potential entrant may delay entry, anticipating that rival entry lowers the expected profitability of a local market. Or, it may accelerate entry if incentives to preempt their rivals are sufficiently strong. In this paper, we establish a setting that offers the opportunity to identify markets which face a credible threat of entry, and we estimate the impact of such a threat on firm actions and industry performance in both the short and long run.

We use the FCC's bi-annual data from 1999 to 2007 on the evolution of local market structures of facilities-based broadband providers at the zip code level. In examining the data, we can identify a potential entrant as *threatened* when a neighboring market houses additional providers of broadband internet service. We then use the timing of entry into the market to understand how a firm's entry strategy is affected by the threat of future competition. Furthermore, we investigate whether delayed entry has long-run implications for the current state of the industry. Specifically, we estimate the extent to which delayed initial entry into a market affects the download speeds available in 2013.

The empirical strategy we adopt is as follows: we construct a latent variable representation of a market's profitability, which depends on observable market characteristics that affect demand and costs, and critically, whether or not a market is threatened by future entry. We then estimate the effect of entry threat on the probability of entry into a market, and on the length of time elapsed until a market is eventually entered. We follow a similar approach to estimate the effect of the number of years of entry delay on the download speeds available in a market in 2013.

Within this framework, we recognize that whether or not a market is threatened is determined by previous entry into neighboring markets. Therefore, if characteristics of neighboring markets which induced entry there are correlated with unobservable characteristics in the market of interest, then entry threat is endogenous. Additionally, if, as we claim, a prospective entrant into a market considers the market structure of neighboring markets when making its entry decision, then it must be true that incumbents in neighboring markets have engaged in a parallel exercise that incorporates their expectations about entry into the market of interest. This reverse causality further aggravates the endogeneity problem of our entry threat indicator.

We address these problems with two remedies. First, we allow markets close to one another to have spatially correlated error terms. Second, we instrument for entry threat using the market attributes of nearby markets. Specifically, these nearby markets are the second order neighbors (that is, neighbors of neighbors) of the market of interest.[1] These attributes affect entry decisions into neighboring markets and therefore, by definition, the threat of entry into the market of interest. At the same time, these attributes can be reasonably considered exogenous to a potential entrant's decision to enter the market of interest. We can reasonably assume that firms did not plan entry decisions more than one step ahead, and therefore that attributes of markets which are two or more zip codes away did not directly affect their entry decision. With these instruments, we estimate parameters of the model, including the extent of spatial correlation, in a generalized method of moments (GMM) framework developed by Pinkse and Slade (1998).

We find evidence that potential entrants place significant consideration on the possibility of future competition when making their entry decision. First, we demonstrate that our measure of entry threat is, in fact, credible: threatened markets are 9% more likely to be entered in the long run. However, in the short run, a market which is threatened by the entry of competitors is 25% less likely to be entered than its unthreatened counterpart. This is a substantial effect, as it represents the net of three separate effects: a threatened market may be less likely to be entered because firms

[1] We do not include second order neighbors which are also direct neighbors when constructing this set.

are unlikely to maintain market power; but on the other hand, it may be more likely to be entered due to preemptive motives; and finally, a threatened market, by definition, has firms nearby that can spill over due to economies of scale. Following this, we show that an open threatened market will, on average, wait about three years longer before being entered by its first broadband provider.

This delayed entry turns out to have important implications for the long-run development of broadband infrastructure. We find that for each additional year that initial entry is delayed, the download speeds available in 2013 fall by 11%. *A priori*, the expected direction of this effect is ambiguous. One might imagine that markets which experience delayed initial entry would receive the latest technology and therefore would have access to faster speeds today. However, nearly all markets in the U.S. had received their initial entrant by 2007, and the prevailing speeds of that time do not even meet the FCC's current definition of broadband. Instead, we argue and provide evidence that markets which experience delayed entry take longer to become competitive and therefore lack the sustained competitive pressure necessary to spur investment in quality improvements.

These findings add to a relatively sparse empirical literature on the effects of entry threat on firm strategies. The theoretical literature is well developed, and has shown that firms facing the threat of a rival's entry have incentives to act preemptively when facing the threat of rivals' entry. Spence (1979, 1981) showed that firms have incentives to enter early and invest to deter competition, and that early entrant advantages are magnified by learning. Milgrom and Roberts (1982) stress the importance of reputation and asymmetric information in deterring entry. Klemperer (1987) showed that firms adopt pricing strategies which take advantage of consumers' cost of switching to a new entrant.

Due to the difficulty in credibly identifying entry threat, there are only a handful of empirical studies on the effects of entry threat on incumbents' behavior. Ellison and Ellison (2011) propose that an incumbent firm's investment may be non-monotone in "market attractiveness" if investments are undertaken to preempt rivals from entering, because preemption is impossible in the most attractive markets. They then find evidence of this behavior in the pharmaceutical industry. Dafny (2005) similarly finds evidence of strategic investment behavior to deter potential entrants in the hospital industry. Goolsbee and Syverson (2008) find that incumbent airlines cut prices dramatically in response to the potential entry of Southwest, and confirm that this action was motivated by preemption rather than accommodation of their future competitor. Prince and Simon (2012) extends Goolsbee and Syverson (2008) to the non-price dimension. They find incumbents' on-time performance actually worsens in response to Southwest's entry threat and actual entry, and attribute this anti-intuitive result to incumbents' incentives to differentiate from the high-performing potential entrant. More recently, Wen and Zhu (2017) find app developers on the Android mobile platform reduce innovation and raise prices in response to Google's entry threat; instead, they shift innovation to unthreatened and new apps. These empirical findings point to a common theme: the incumbents' actions when facing entry threat depend on whether the entry threat can be deterred. If entry threat cannot be deterred, the incumbent faces a lowered expected profit stream as if entry threat is actual entry.

This insight carries over when we study potential entrants facing entry threat from other potential entrants. Potential entrants, like incumbents, may be incentivized to quickly enter a threatened market in an effort to preempt their rivals. But, they may also be motivated to delay entry, fearing that the market may become competitive and therefore less profitable in the future. Which of these effects dominates is therefore an empirical question, depending on the strength of the entry threat. Seamans (2012) shows that incumbent cable television providers, acting as potential entrants in this case, were more likely to begin offering internet service in areas where the local government might provide internet service in the future. Conversely, in our setting, we find that the effect of expected future competition dominates. We provide evidence that even after controlling for factors that influence demand and costs, internet service providers delay entry into markets that are threatened by future entry of rivals.

More broadly, our work relates to the literature on the effects of market structure on quality provision. Theory predictions on the effect of market structure on quality provision is less clean cut than that on prices. Matsa (2011) shows that supermarkets facing more intense competition have better product availability. Mazzeo (2003) finds average flight delays are shorter in more competitive markets; Prince and Simon (2017), however, find airline mergers have negligible impacts on airlines on-time performance measures. More relevant to broadband, Molnar and Savage (2017) find competition in wireline ISPs increases wireline Internet speed. Our work adds a new angle to this line of work: we focus the *past* strategic actions of firms, which translate into meaningful differences in the quality of internet access available more than a decade later. Our results hold even after controlling for current market structure.[2] In other words, firms past actions, which determine past market structure, have independent effects on both the market structure and firm performance we face today.

2 The Evolution of Broadband Internet and the Digital Divide

The 1996 Telecommunications Act was passed with the goal of encouraging competition in local telecommunications markets, largely by removing barriers to entry and by requiring incumbent firms to lease their lines to competitors. The act has been at least partially successful in achieving this goal, as several papers have investigated strategic interaction among competitors and the welfare effects of new entry into local telecommunications markets. Greenstein and Mazzeo (2006) found that telephone firms differentiate themselves strategically when entering markets; Economides, Seim, and Viard (2006) show that households in the state of New York benefit significantly from this resulting product differentiation. As shown in figure 1, the fraction of zip codes with access to at least one broadband provider rose from 58% to 93% between 1999 and 2007, with most of this growth occurring by 2003. Furthermore, the 93% of zip codes which had broadband in 2007 accounted for over 99% of the U.S. population. As a result, the question of interest is not if, but rather when, individuals obtained access to broadband internet.

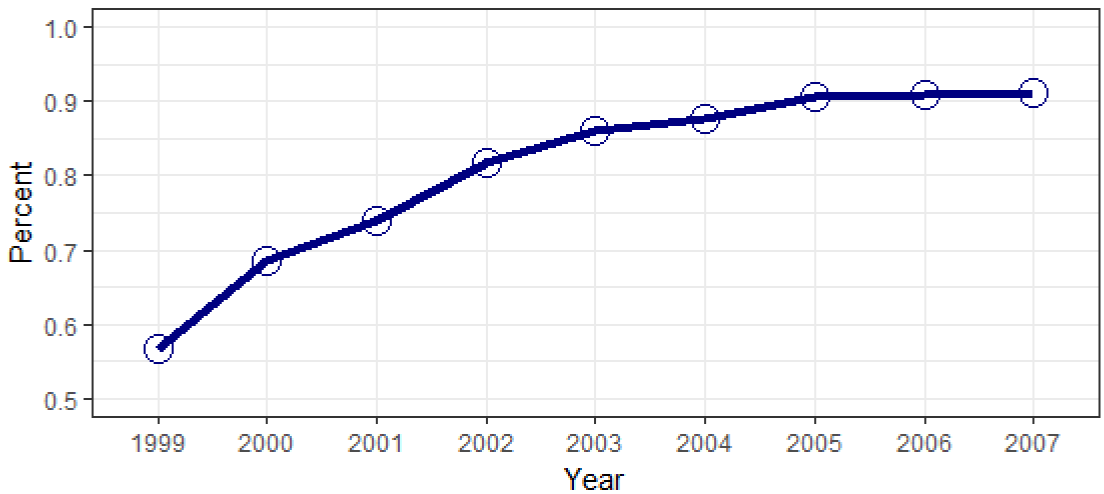
2.1 Firm Types and Quality Improvements

In the United States, internet service is provided predominantly by two types of firms, cable television and telephone companies. Cable firms provide broadband service using hybrid fiber-coaxial cable networks, and telephone companies over digital subscriber lines (DSL). Both types of firms provide internet service primarily using the lines put in place for their preexisting cable television and telephone services, retrofitted to allow for the bilateral transfer of data required for internet usage.

Since its inception, the speeds of household broadband internet connections have continually improved. Cable firms have improved speeds by adopting common standards for data transmission, known as DOCSIS, the current version of which allows for many channels to be bonded together

[2] Our results on current market structure corroborate the findings in Molnar and Savage (2017).

Figure 1: Fraction of Zip Codes with Broadband Internet



Source: FCC Form 477

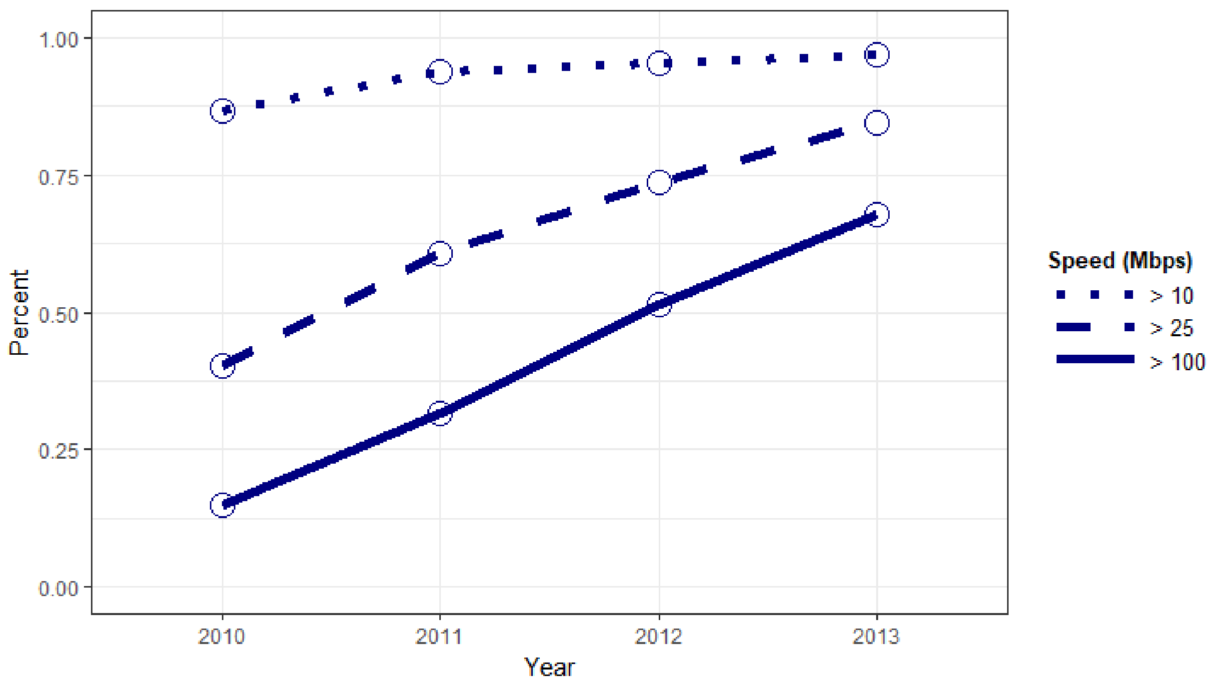
and used by a single subscriber. At the same time, cable firms have expanded their use of fiber-optic cables, which increase the available bandwidth and reduce congestion. Telephone firms have also deployed fiber-optic cables throughout their networks. This strategy is particularly important for them, as transmitting data at high speeds over long distances using their existing telephone wires is physically impossible. In some areas, cable and/or telephone firms have constructed networks which consist exclusively of fiber-optic cables, in what is known as fiber-to-the-premises.

As shown in figure 2, the fraction of zip codes with download speeds of at least 10 megabits per second (Mbps) increased from 87% to 97% from 2010 to 2013. Over the same period of time, the fraction of zip codes with download speeds of at least 25 Mbps, the FCC's current definition of broadband speeds, rose from 40% to 84%. Finally, the share of zip codes with download speeds of at least 100 Mbps grew from just 15% to 68%.

2.2 Digital Divide and Government Policy

Despite the dramatic rise in broadband availability between 1999 and 2007, this deployment did not occur evenly across the country. In 2003, zip codes that did not yet have access to broadband internet, on average, had household incomes that were $7,340 less than those with broadband internet; they also had a rate of college graduation that was 9 percentage points lower and were far more likely to be in rural areas. The U.S. census records the percentage of each zip code which is

Figure 2: Fraction of Zip Codes with Broadband Speeds



Source: National Broadband Map

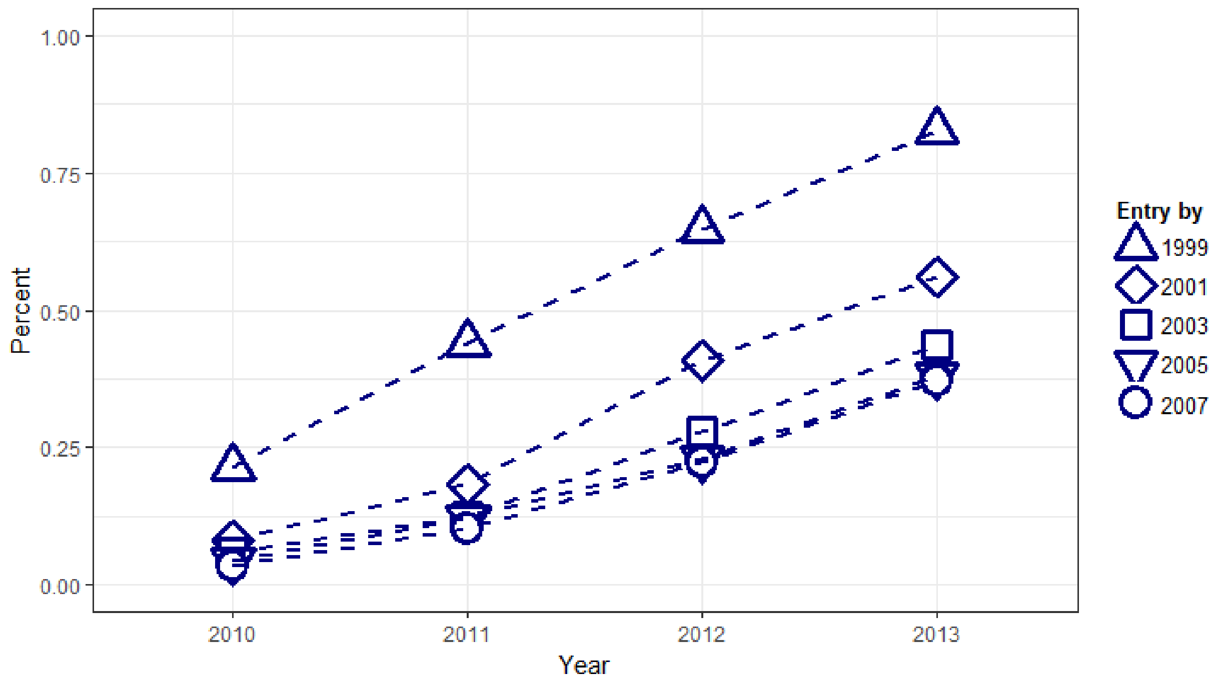
considered rural, and markets without broadband in 2003 were, on average, 87% rural, while those with broadband were only 59% rural.[3]

Similarly, the improvements in speed between 2010 and 2013 were not uniform. In 2014, zip codes without access to download speeds of at least 25 Mbps, on average, had $10,505 lower household incomes, college graduation rates which were 7 percentage points lower, and were 37 percentage points more rural.

The timing of a market's initial availability of broadband internet and its present-day speeds are closely related. Figure 3 shows the trajectory of availability of download speeds of 100 Mbps, broken down by year of initial entry. Markets which were initially entered earlier were more likely to have access to 100 Mbps sooner; and, perhaps more interestingly, this gap has widened over time. Of course, this relationship may simply be the result of the demographic correlations outlined earlier in this section; or, it may be the case that the timing of initial entry has a causal impact upon long-run broadband quality. If markets that are entered later do not become competitive until

[3]Comparable statements can be made about the set of markets without access to broadband in any particular year. 2003 is in no way unique is this regard.

Figure 3: Fraction of Zip Codes with Access to 100 Mbps by Year of Initial Entry



Source: National Broadband Map

later still, and sustained competition leads to quality improvements, then this delayed entry will directly impact broadband quality in the long run. We investigate this relationship in our empirical analysis and find evidence to support this mechanism.

While demographic differences can explain a great deal of the disparity in internet availability and quality provision, the strategic entry decisions of firms may serve to exacerbate this issue. This inequality in access to and quality of broadband internet has been termed the "digital divide", and has consistently been a major policy concern in the United States. The Communications Act of 1934 established the goal of Universal Service in telecommunications, which meant that quality services should be made universally available at just and affordable rates without discrimination by income or ruralness. The 1996 Telecommunications Act codified these principles to apply to high-speed internet service. The FCC oversees a number of programs which aim to accomplish this goal, including the Connect America Fund, which subsidizes the expansion of ISPs' networks, and the Lifeline Program, which subsidizes prices paid by low-income households.

3 Data and Definitions

Our analysis is based primarily on two sources of data compiled by the FCC and in partnership with the National Telecommunication and Information Administration (NTIA). The first data set is the FCC's Form 477, collected bi-annually by the FCC beginning in 1999, and made available from 1999 to 2007. The FCC requires every facilities-based provider with at least 250 high-speed lines[4] to report its presence in a given zip code as long as it serves at least one customer there. The FCC releases summary statistics to the public aggregated to the zip code level. From these snapshots of market structure, we can observe the timing of net entry and exit of broadband providers over six month intervals. In our study, we only use the December data, in order to allow sufficient time for changes in market structure to occur, and so that our net entry and exit is measured over one year intervals.

This data set, covering the entire United States and spanning multiple time periods, provides a rare opportunity for researchers to study market evolution in the early stages of a rapidly-growing service industry. However, we must acknowledge some drawbacks of the data. It lacks firm identities, so we can only observe net entry rather than actual entry and exit of firms. It also means that our inference of entry threat is derived from observations of the number, but not the identities, of incumbent providers across markets. We also cannot distinguish between different types of broadband services such as cable and DSL, and so we cannot test whether the effect of entry threat differs by provider type. Furthermore, very small providers (with less than 250 high-speed lines) are not required to report to the FCC, generating measurement errors in our econometric analysis.[5] Finally, for confidentiality reasons, the data indicates the presence of 1, 2, or 3 providers with a single indicator. As a result, we focus our analysis on the decision of the first entrant, rather than subsequent entries. Despite these limitations, the breadth and depth of the data generate interesting inferences about entry decisions which are not possible using other available data.

Our second data set is the source data from the 2013 National Broadband Map, which was collected through the State Broadband Initiative, a program overseen by the NTIA. This data provides information about the current state of the U.S. broadband infrastructure, indicating the

[4]High-speed lines are defined as those that provide speeds exceeding 200 kilobits per second (kbps) in at least one direction.

[5]Fortunately, few providers fall into this category. Paradyne (2000) shows that entry is not profitable unless there are at least 200 lines in a DSL service area.

identities of each firm in each census block, along with their local technology and maximum advertised download and upload speeds. Maximum advertised speeds are reported as a categorical variable, whose values represent ranges of speeds; we replace these values with the median value of the relevant range. In order to pair this data with the early FCC data, we aggregate observations to the zip code level by taking a population-weighted average across the blocks within a zip code.

Finally, we use three auxiliary data sets: we use demographic characteristics from the 2000 Census and the 2010 American Community Survey (ACS), based upon zip code tabulation areas (ZCTAs).[6] The variables selected include population, average income, education, age, ethnicity, commuting distance, and population density, all of which affect local demand for and/or the cost of providing internet service. Finally, we use the number of business establishments for each zip code from the 2000 Zip Code Business Patterns data, which serves as our measure of local business activity. Descriptions and summary statistics for these variables are provided in section 3.5.

3.1 Market Definition

In any service industry, consumer mobility determines the boundaries of a local market. This can be quite challenging, as researchers typically do not have good data on consumers' willingness to travel for desirable services. The broadband market, however, is fairly unique; consumers have no mobility at all, as they can only purchase a subscription from providers offering service at their residence. Therefore, we avoid the problem of blurred market boundaries which complicates many studies of market structure.[7]

Fortunately, the FCC data offer a natural definition for markets by indicating the number of firms offering service within each zip code. Since households cannot subscribe to a broadband provider who does not serve their zip code, this provides us with a clean market boundary. With that said, one might wonder whether broadband providers make entry decisions at such a fine geographic level. They may instead make decisions at the city, county, or even state level, though it would take years to roll out full coverage to these larger areas. This type of long-run strategy would not only compromise our market definition, but would also threaten the validity of the

[6]ZCTAs, defined by the Census Bureau, are not identical to zip codes, which are defined by the U.S. Postal Service. However, all zip codes in the FCC data do have a match in the 2000 Census data.

[7]Complete consumer immobility does, however, have the potential to create a problem of its own. If we define a local market to be too large, a provider within the market may not actually offer service to all households.

instruments we propose in section 4.6. Furthermore, the relevant market definition in the long-run likely varies considerably across firms, as some broadband providers have a national presence, while others serve only one city.

For these reasons, we focus on the short-run entry decision of firms, the gradual "rolling out" process of broadband providers. Specifically, we consider a broadband provider's marginal decision to expand service to one more local market. Since expanding service to a local market involves sunk costs, we can define the boundaries of the market by the nature of those costs. In the broadband industry, these sunk costs are the costs of deploying the so-called "last mile" of infrastructure. Firms must lay or renovate coaxial cables and telephone wires, as well as build or modify switching and distribution centers, cable television head ends, and DSL access multiplexers. The distance between an end-user and a broadband provider is a primary factor in determining which neighborhoods can be served, particularly for telephone providers. This physical constraint limits the radius of a local market, as DSL can be provided reliably within a radius of 18,000 feet, or about 3.4 miles from the firm's central office. This again suggests that zip codes are the appropriate geographic approximation of a local broadband market, as the typical zip code has a radius of between 3 and 4 miles, according to the 2000 U.S. Census.

3.2 Neighboring Market Definition

Our data indicates the latitude and longitude of the centroid of each zip code in the United States. The distance between the centroids of two zip codes forms the basis of our definition of neighboring markets. However, this distance alone ignores the geographic sizes of the zip codes; in fact, two large zip codes could border one another but have centroids which are far apart. In order to address this issue, we assume that all zip codes are circular and calculate their radius as follows:

$$r_m = \sqrt{\frac{area_m}{3.14}} \tag{1}$$

where r_m is the radius of market m and $area_m$ is the geographic area of market m. We then define market m and market m' to be neighbors according to the following definition:

$$neighbors_{m,m'} = \begin{cases} 1 & \text{if } distance_{m,m'} \leq 3 + \max\{r_m, r_{m'}\} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where $distance_{m,m'}$ is the distance between the centroids of markets m and m'. Put more simply, we define two markets to be neighbors if the distance from the centroid of one market to the boundary of the other is less than 3 miles. The choice of 3 miles is somewhat arbitrary, but supported by the physical limitations of DSL technology. A telephone provider with a central office located at the centroid of market m could feasibly serve market m' if the boundary of market m' was within about 3 miles of the centroid of market m, as noted in the previous section.[8]

3.3 Entry Threat Definition

In the broadband industry, there are enormous economies of scale in building out a network. As a result, an incumbent provider will find it much easier to spill over into an adjacent market than to enter a more distant market. Therefore, we define a market, m, to be *threatened* if at least one rival firm operates in some neighboring market, m', but not in market m. Formally, the entry threat status of market m at time t is

$$EntryThreat_{mt} = \begin{cases} 1 & \exists\ m' \text{ s.t. } neighbors_{m,m'} = 1 \text{ and } N_{m't} > 1 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where $neighbors_{m,m'}$ is as defined in equation (2) and $N_{m't}$ is the number of firms serving market m' at time t.[9]

[8]To test the sensitivity of our analysis to this choice, we replace the value of 3 in equation (2) with alternative values and obtain result which are qualitatively unchanged.

[9]Because our data is censored such that all markets with 1, 2, or 3 firms are recorded as a 1, we can only detect that a market has more than 1 firm if that market has at least 4 firms. $EntryThreat_{mt}$ is defined subject to this limitation.

Table 1: Neighbors Summary Statistics

Variable	Mean	Standard Deviation	Min	Median	Max
# Neighbors	2.611	1.533	1	2	28
Entry Threat	0.069	0.253	0	0	1
# Markets: 7,642					

3.4 Sample Selection

The FCC's Form 477 data contains deployment data on the universe of the 31,862 zip codes in the United States. From this set, we drop 1,784 markets which do not have a neighboring market. We also drop 64 markets which have more than 30 neighbors; these markets cover very little geographic area and therefore do not fit our market definition. Finally, there are 1,799 markets which are missing demographic data, and so we drop these observations from our sample, leaving us with a total of 28,207 markets.

Because the focus of our analysis is on the decision of the first entrant to enter an open market, and because our goal is to understand the effect of the threat of future competition on firms' entry decisions in the early rollout of broadband infrastructure, we restrict attention to markets which were unserved in the year 2000,[10] leaving us with 8,476 markets.

Finally, there are some zip codes which we do not observe in the 2013 National Broadband Map data. In the interest of maintaining a consistent set of observations across all specifications, we drop these from our sample, leaving us with 7,642 markets.

3.5 Summary Statistics

Summary statistics for neighbors and entry threat are shown in table 1. On average, a market has 2.61 neighbors, and this varies between 1 and 28 for all markets in our sample. Of the 7,642 markets in our sample, about 7%, or 535 markets are threatened.

Table 2 presents summary statistics for each of the market characteristics included in our specifications, broken down by entry threat status. Threatened and unthreatened markets are quite similar across most dimensions, though threatened markets typically have larger populations, are less rural, more densely populated, and have more businesses.

[10] Our data begins in 1999, and would therefore permit us to study one year earlier, but only a tiny fraction of open markets were threatened at that time, which affords our estimates very little power. For robustness, we carry out our full analysis for 1999 and find qualitatively similar results.

Table 2: Demographic Summary Statistics

Variable	Mean | Threat = 0	Mean | Threat = 1	t Statistic
Population	1,159.095	1,784.641	3.018
% Black	0.050	0.036	-2.491
% Hispanic	0.038	0.059	3.272
% Am. Indian	0.023	0.007	-7.655
% Asian	0.003	0.008	4.411
ln(Median income)	10.361	10.629	14.784
% College	0.364	0.433	7.436
Household size	2.571	2.601	1.797
% Female	0.498	0.503	2.806
% Senior	0.327	0.310	-3.647
% Work from home	0.062	0.037	-11.074
% Long commute	0.199	0.188	-1.869
% Rent	0.196	0.226	4.650
% Phone	0.951	0.980	17.086
% Rural	0.946	0.599	-17.337
ln(Population density)	3.262	5.862	33.375
ln(Business density)	2.804	3.221	8.781
# Markets	7,115	527	

Table 3: Outcome Summary Statistics

Variable	Mean | Threat = 0	Mean | Threat = 1	t Statistic
Short-run Entry	0.341	0.182	-8.943
Long-run Entry	0.906	0.983	11.634
Entry Delay	3.468	6.476	19.770
Mean 2013 Download Speed (Mbps)	72.685	140.998	13.589
# Markets	7,115	527	

Despite these seemingly attractive features, in the short-run, threatened markets are entered much less often than their unthreatened counterparts. Table 3 shows that threatened markets were entered about half as often between 2000 and 2001. In addition, markets which were open in 2000 waited, on average, 3 years longer to be entered if they were threatened. In the long run, however, threatened markets were more likely to be entered, as 98% had access to at least 1 provider in 2013.

4 Empirical Framework

4.1 Entry in the Short Run

When modeling the decision of a firm to enter an open market, we consider a static entry game in the spirit of Bresnahan and Reiss (1991). In this setting, firms make their entry decisions and then receive continuation values which depend on the actions of other firms. We choose this simpler model over a full-fledged dynamic one because firms faced enormous uncertainty about their rivals' behavior. The industry was still in its infancy, which meant that industry norms had not yet formed and that the turnover rate was very high. Therefore, we do not believe that writing down an explicit value function, which would require firms to make predictions about the entire future evolution of the market, is appropriate for this setting.

Consider the decision of the first firm to enter a market, m, which contains no firms at time t. Firms are ranked from 1 to P, where P is the total number of potential entrants, on the basis of their efficiency. We assume that firms are sequentially given the opportunity to enter the market, and that a more efficient firm will always enter earlier than a less efficient one. This assumption ensures that at any point in time, there will be at most one potential entrant, which we label firm p.

At the start of period t, firm p observes the state of the market and decides whether the expected discounted value of the future profit stream is high enough to support entry. Expected profitability is calculated based upon market demand, cost of providing service, and anticipated future market structure. Potential entrant p forms its expectation about the future market structure of market m based upon the market structures of neighboring markets. As defined in equation (3), firm p considers market m to be threatened if at least one rival firm operates in a neighboring market but not in market m.

The expected discounted value of future profits of potential entrant p from entering market m at time t is

$$\mathbb{E}(\Pi_{mt}^{p}) = \alpha_{0t} + X_m\alpha_{1t} + \alpha_{2t}EntryThreat_{mt} + \nu_{mt}^{p} \tag{4}$$

This reduced form representation of expected profits states that profits depend on a vector of market attributes (X_m), the threat of future competition, and a stochastic error term (ν_{mt}^{p}) which includes factors influencing profits that are observed by firm p but not by the econometrician. Firm p will therefore enter market m at time t if and only if $\mathbb{E}(\Pi_{mt}^{p}) \geq 0$. We represent this entry decision with a binary variable, D^p_{mt}, where a value of 1 indicates entry. Therefore,

$$Pr(D^p_{mt} = 1) = F(\alpha_{0t} + X_m\alpha_{1t} + \alpha_{2t}EntryThreat_{mt}) \tag{5}$$

where $F(\cdot)$ is the cumulative distribution function of an error term which follows the distribution described in section 4.5.

Market-specific variables which we expect to influence variable profits and fixed operating costs are represented by X_m. Market size, as measured by population, is a key element, as shown by Bresnahan and Reiss (1990, 1991). Additionally, local characteristics such as sex, race, age, income, commuting patterns, and business activities are all likely to shift demand for broadband internet. Population density is an important factor in determining fixed costs, as rolling out wires in sparsely-populated areas is very expensive.

The intent of α_{2t} is to capture firm p's concern over a competitive future market structure. However, because we do not observe firm identities, when $EntryThreat_{mt} = 1$, it is possible that firm p is itself one of the firms present in a neighboring market. In such a case, firm p can more easily enter market m, and α_{2t} will pick up this positive spillover effect. Therefore, α_{2t} represents the net of this spillover effect and any strategic effects of entry threat. Though the sign of the spillover effect is known, the direction of the strategic effect is *ex-ante* unclear. Firms may be likely to quickly enter a threatened market in order to preempt their competition; or, they may be less likely to enter because the likelihood of future competition lowers their expectation of the market's future profitability. Unfortunately, we cannot separately identify these effects; but, since the spillover effect is known to be positive, a negative $\hat{\alpha}_{2t}$ would indicate that the presence of rivals in neighboring markets makes potential entrants less likely to enter a market, and that this effect dominates both the spillover and (potential) preemption effects.

4.2 Entry Delay

If the threat of future competition makes firms less likely to enter a market in the short run, then the natural follow up question becomes: how long do firms delay entry into a market as a result of this threat? To answer this, we estimate the following model:

$$EntryDelay_{mt} = \beta_{0t} + X_m\beta_{1t} + \beta_{2t}EntryThreat_{mt} + \omega_{mt} \tag{6}$$

where $EntryDelay_{mt}$ is equal to the number of years elapsed from time t until market m receives its first entrant. X_m is the same set of observed market characteristics affecting market m's profitability, and ω_{mt} are unobservable shocks affecting entry into market m. β_{2t} represents the degree to which firms delay entry into market m in response to the threat of future competition.

As in the previous model, we cannot give a structural interpretation to β_{2t}, as the parameter captures the net of all reasons why entry threat would effect the delay of entry into a market. However, even in the reduced form, the parameter is very telling: a positive β_{2t} informs us that on average, firms delay entry into a market which is threatened by competitors from neighboring markets.

4.3 Broadband Speeds in the Long Run

Finally, we investigate whether the early evolution of the broadband industry has had long-term effects. Nearly all Americans have access to broadband internet today, so it is important to ask whether the delay in gaining access experienced by many still matters. To this end, we estimate the effect of entry delay on maximal modern-day download speeds; specifically, we estimate the following model:

$$\begin{aligned} \log(Speed_{m,2013}) = \delta_0 + X_{m,2013}\delta_1 + \delta_{2t}EntryDelay_{mt} + \\ + \delta_{3t}ln(\#ISPs)_{m,2013} + \eta_{mt} \end{aligned} \tag{7}$$

where $Speed_{m,2013}$ is the maximum advertised download speed (in Mbps) available in market m in 2013, $X_{m,2013}$ are the 2013 values of the same attributes of the previous specifications, $EntryDelay_{mt}$ is the number of years elapsed from time t until market m is entered, $ln(\#ISPs)_{m,2013}$ is the log of the number of ISPs present in the market in 2013, and η_{mt} are unobservable shocks affecting broadband speeds.

It is important that we control for the number of ISPs present in this specification. Markets which experienced entry delay are, on average, less competitive even today. Therefore, without this control, our estimated effect of entry delay could be fully attributable to the current market structure. While this is interesting in its own right, we are instead interested in whether the early evolution of the industry has a *direct* impact on present-day outcomes.

4.4 Entry in the Long Run

We intend for our measure of entry threat to capture the likelihood of eventual entry into market m. Therefore, if this measure is credible, it must be the case that threatened markets are *more* likely to be entered in the long run, regardless of the sign of the short-run entry threat effect. To test this, we estimate the following model:

$$Pr(LongRunEntry_{mt}) = F(\gamma_{0t} + X_m\gamma_{1t} + \gamma_{2t}EntryThreat_{mt}) \tag{8}$$

where $Pr(LongRunEntry_{mt})$ is the probability that market m is entered between time t and 2013,[11] and X_m and $EntryThreat_{mt}$ are as defined in equation (4). The function $F(\cdot)$ is the cumulative distribution of an error term which follows the distribution described in the following section.

4.5 Modeling Spatial Correlation in the Errors

u_{mt} is a random shock, representative of the error terms ν_{mt}, ω_{mt}, and η_{mt} of equations (4), (6), and (7), affecting decisions made in market m at time t. These shocks may capture regional spikes in demand, local economic downturns, regulatory hurdles, and any other factors which are not controlled for through observable market characteristics. As such, it is likely that these shocks are not isolated to a single zip code, but rather are correlated with the shocks experienced by other nearby markets. To allow for this possibility, we impose the following structure on the error terms:

$$u = \psi Wu + \varepsilon \tag{9}$$

[11] We also estimate a specification where the outcome is a binary variable equal to 1 if and only if market m contains at least 4 firms by 2013, in order to test whether threatened markets are more likely to become competitive and obtain nearly identical results.

u is an $M \times 1$ vector of error terms, where M is the total number of markets; ψ is a scalar measuring the degree of spatial correlation; W is an $M \times M$ symmetric matrix with elements w_{ij} such that w_{ij} is a binary variable equal to 1 if and only if $i \neq j$ and $neighbors_{ij} = 1$; ε is an $M \times 1$ vector of identically and independently distributed random variables such that

$$\varepsilon \sim N(0, I_M) \tag{10}$$

where I_M is the identity matrix with dimension M. Note that m and t subscripts have been suppressed in equations (9) and (10) for ease of notation.

The ψ term captures spatial correlation in the errors, u. If $\psi = 0$, then there is no spatial correlation and each u_i is simply drawn from the normal distribution in equation (10). If $\psi \neq 0$, then spatial correlation exists, and there are unobservable factors which influence firms' decisions that are correlated across neighboring markets.

Given equation (9), the variance-covariance matrix of u is

$$V(u) = [(I_M - \psi W)'(I_M - \psi W)]^{-1} \tag{11}$$

and is heteroskedastic if $\psi \neq 0$. Therefore, if there is spatial correlation in the errors, the maximum likelihood estimates of the probit model will be inconsistent. To deal with this, we use the generalized method of moments (GMM) approach developed by Pinkse and Slade (1998), which yields consistent estimates of the parameters under spatial correlation.

In order to construct the residuals necessary to estimate equations (5) and (8), we follow Pinkse and Slade (1998) to define the generalized error term as

$$u_{mt}(\theta) = [D_{mt} - \Phi(G_{mt}(\theta))] \frac{\phi(G_{mt}(\theta))}{\Phi(G_{mt}(\theta))[1 - \Phi(G_{mt}(\theta))]} \tag{12}$$

where θ represents α or γ, D_{mt} represents entry in the short or long run, $G_{mt}(\theta) = \frac{\tilde{X}_{mt}\theta}{\nu_m(\psi)}$, $\tilde{X}_{mt}\theta$ represents the term inside $F(\cdot)$ in equations (5) or (8), $\nu_m(\psi)$ is the square root of the m^{th} diagonal element of $V(u)$, and $\phi(\cdot)$ and $\Phi(\cdot)$ are the density and cumulative distribution functions of a standard normal random variable. The generalized residuals are defined analogously.

4.6 Endogeneity of Entry Threat

The interconnected nature of firms' decisions across markets gives rise to two sources of potential endogeneity in our entry threat variable. First, entry threat is not exogenous if the error terms are spatially correlated across neighboring markets. To see why, consider two isolated neighboring markets, m and m'. Given equation (4), unobservable factors in the error term of market m' influence firms' entry decisions there; and, given equation (3) these entry decisions determine whether or not market m is threatened. Therefore, if the the error terms of market m and m' are correlated, then the entry threat status and error term of market m are correlated.

Second, if firms do indeed consider the threat of future competition when making entry decisions, then our entry threat variable cannot be exogenous, as firms in neighboring markets each make entry decisions while considering the threat of spillover from the other. To see this, note that unobservable factors in the error term of market m influence firms' entry decisions there; these entry decisions then determine whether or not market m' is threatened; the entry threat status of market m' then influences firms' entry decisions there, which in turn determine whether or not market m is threatened. Therefore, we can conclude that the entry threat status and error term of market m must be correlated.

Notably, this second source of endoegeneity exists regardless of the presence of spatial correlation, as long as entry threat has a direct effect on entry decisions. These two sources of endogeneity affect each of our empirical specifications and must be dealt with in order to give our estimates a causal interpretation.

In the spirit of Pinkse and Slade (1998), we use the average market attributes of all of a market's *neighbors'* neighbors as instruments for entry threat. These characteristics will affect entry into a market's neighbors, but should have no direct effect on the decision to enter the market itself. To be concrete, suppose that market m' has a neighbor, m'', but that market m and market m'' are not themselves neighbors. The attributes of market m'' clearly affect whether market m'' contains any firms. Additionally, a firm's presence in market m'' increases its likelihood of spilling over into market m', which then creates an entry threat for market m. In order for these instruments to be exogenous, firms may consider the attributes of neighboring markets when making their entry decision, but they must not consider the attributes of other, further away markets. In other words, firms can be forward-looking but must be sufficiently myopic. In principle, we could allow firms to consider any number of steps ahead and construct the appropriate set of instruments.

4.7 Estimation

In order to deal with both the presence of spatial correlation and the endogeneity of our key variable, we adopt the generalized method of moments estimation framework of Pinkse and Slade (1998). We form the moment conditions using a set of L instruments, Z, such that $\mathbb{E}[Z'u(\alpha)] = 0$. Z is therefore an $M \times L$ matrix with L greater than or equal to the length of the parameter vector, θ.[12] When necessary, we use the generalized error defined in equation (12). The sample analogue of the moment is

$$S(\theta) = \frac{1}{M} Z'\hat{u}(\theta) \tag{13}$$

When the model is just-identified, we solve for the $\hat{\theta}$ such that $S(\hat{\theta}) = 0$. When the model is over-identified,

$$\hat{\theta} = \arg\min_{\theta} S'(\theta)\Omega S(\theta) \tag{14}$$

where Ω is an $L \times L$ positive definite weighting matrix.[13]

Under this procedure, even when $\psi \neq 0$, $\hat{\theta}$ is consistent and asymptotically normal. We then estimate the variance-covariance matrix of $\hat{\theta}$ by using the following property of $\hat{\theta}$:

$$\sqrt{M}(\hat{\theta} - \theta) \sim N(0, [B_2(\theta)]^{-1} \frac{\partial S'(\theta)}{\partial \theta} \Omega B_1(\theta) \Omega \frac{\partial S(\theta)}{\partial \theta'} [B_2(\theta)]^{-1}) \tag{15}$$

where $B_1(\theta) = M\mathbb{E}[S(\theta)S'(\theta)]$ and $B_2(\theta) = \frac{\partial S'(\theta)}{\partial \theta} \Omega \frac{\partial S(\theta)}{\partial \theta'}$.

[12] Note that even when all right hand size variables are exogenous, we still need one extra instrument in order to identify ψ.

[13] We use the optimal weighting matrix for Ω, which we construct according to the following steps: first, we get a consistent GMM estimate, $\hat{\theta}_1$ by using $\Omega = I_M$ in equation (14); second, we construct $\hat{\Omega} = ME[S(\hat{\theta}_1)S'(\hat{\theta}_1)]$.

5 Results

5.1 Is Entry Threat Credible?

We have argued that the broadband industry has a natural indicator for the threat of future entry into a market, the presence of other firms in a neighboring market. The enormous localized fixed costs of broadband infrastructure ensure that entering nearby markets is far more efficient than entering more distant markets. Therefore, we should see that markets which are threatened in the early stages of the rollout are more likely to be entered in the long run. In support of this claim, we present the results of estimating equation (8) in table 4. The first two columns report the results of estimating a linear probability model; the first column was estimated with ordinary least squares, while the second is estimated using neighbors' neighbors' attributes as instruments. The third column reports the average partial effects calculated from the results of the GMM estimation procedure described in section 4.7, which controls for spatial correlation in the error terms.

We find that after accounting for the endogeneity of entry threat, markets which are threatened in the year 2000 are more likely to be entered by 2013. Under our preferred specification in column (3), we find that entry threat increases the long run probability of entry by 9 percentage points. This finding is consistent with the idea that firms can more easily spill over into areas where the firm already has a foothold, and critically, demonstrates that this threat of entry is "real" in a very material way. Our results also illustrate the importance of addressing our endogeneity concerns, as the OLS estimates in column (1) suggest that there is no statistically significant effect of entry threat on long run entry. Furthermore, we find evidence of substantial spatial correlation in the error terms. We estimate ψ in equation (9) to be 1.323 and easily reject the null hypothesis of no spatial correlation, or $\psi = 0$.

5.2 Does the Threat of Future Competition Delay Entry?

Equipped with evidence that the threat of entry does indeed lead to entry in the long run, we turn to the question of how potential entrants revise their entry strategies in light of the threat of future competition. The results of estimating equation (4) are reported in table 5 and demonstrate that firms were less likely to enter a threatened market, other things equal. This finding is robust across all specifications. As before, we report results of estimating a linear probability model in columns

Table 4: Probability of Long-run Entry

	(1)	(2)	(3)
Entry Threat	-0.002	0.123***	0.088***
	(0.014)	(0.040)	(0.005)
Population (1,000)	0.009***	0.009***	0.026***
	(0.002)	(0.002)	(0.005)
Percent Black	-0.089***	-0.089***	-0.137***
	(0.024)	(0.024)	(0.024)
Percent Hispanic	-0.161***	-0.170***	-0.189***
	(0.03)	(0.031)	(0.031)
Percent American Indian	-0.344***	-0.351***	-0.246***
	(0.040)	(0.040)	(0.039)
Percent Asian	0.089	0.105	2.977**
	(0.149)	(0.150)	(1.299)
log(Median Household Income)	0.069***	0.056***	0.037**
	(0.014)	(0.014)	(0.015)
Percent Graduated College	-0.053*	-0.072**	-0.046
	(0.028)	(0.029)	(0.036)
Average Household Size	0.016	0.014	0.009
	(0.017)	(0.017)	(0.021)
Percent Female	0.239**	0.257**	0.305***
	(0.101)	(0.102)	(0.098)
Percent Senior	0.025	0.012	0.009
	(0.061)	(0.061)	(0.068)
Percent Work from Home	0.150***	0.141**	0.153**
	(0.056)	(0.056)	(0.068)
Percent Long Commute	-0.322***	-0.330***	-0.209***
	(0.025)	(0.025)	(0.026)
Percent Rent	0.070*	0.061	0.020
	(0.038)	(0.038)	(0.043)
Percent with Phone	0.190***	0.182***	0.019
	(0.066)	(0.067)	(0.058)
Percent Rural	-0.019	0.010	-0.251
	(0.016)	(0.018)	(0.161)
log(Population Density)	0.016***	0.011***	0.016***
	(0.002)	(0.003)	(0.003)
log(Business Density)	-0.004	-0.005	-0.004
	(0.004)	(0.004)	(0.004)
ψ	-	-	1.323***
	-	-	(0.221)
Instruments: Neighbors' Neighbors' Attributes	N	Y	Y
Allow for Spatial Correlation	N	N	Y
# Markets	7,642	7,642	7,642

(1) and (2), and the GMM estimation controlled for spatial correlation in column (3). We use the GMM point estimates to calculate that, on average, entry threat decreases the probability that a market is entered by 25 percentage points.

Since firms appear reluctant to enter threatened markets, we next investigate the persistence of this effect. Rather than looking solely at the entry decisions of a single time period, we estimate the effect of entry threat on the length of time elapsed until a market is entered, in order to take advantage of our panel of data. We report the results of estimating equation (6) in table 6.

We find that an open market which is threatened in the year 2000 is entered, on average, about 3 years later that its unthreatened counterpart. For perspective, the average unthreatened market which was open in 2000 waited about 3.5 years until being entered, so this estimated effect represents a significant delay.

5.3 Does Delayed Entry Affect Broadband Speeds in the Long Run?

Despite the delay created by internet service providers' reluctance to compete against their rivals, over 95% of zip codes had at least one internet service provider as of 2013. It is then natural to ask whether this delay really mattered, or whether "time heals all wounds." We therefore estimate the impact of delayed initial entry on the download speeds available in 2013, more than 10 years after the start of our sample. We report the results of estimating equation (7) in table 7.

We find evidence that delayed entry early in the rollout of the U.S. broadband infrastructure had a significant impact on download speeds available today, specifically that each additional year that a market remains open translates into an 11% decrease in present-day download speeds. Remarkably, this result is true even when controlling for the current number of firms serving a market. This means that the mechanism for this effect is not simply that markets which are entered later are still less competitive today and therefore have faster available speeds today. We do find that the number of firms serving a market has a significant positive impact on local download speeds; we estimate that doubling the number of ISPs in a market translates into a 108.4% increase in download speeds.[14] This finding is consistent with Molnar and Savage (2017). We estimate a stronger effect, though our results are not directly comparable due to specification differences. But interestingly,

[14]Because we estimate a log-log specification, our results imply that a 100% increase in the number of ISPs in a market leads to a 108.4% increase in download speeds.

Table 5: Probability of Short-run Entry

	(1)	(2)	(3)
Entry Threat	-0.111***	-0.171***	-0.250***
	(0.023)	(0.066)	(0.057)
Population (1,000)	0.067***	0.067***	0.069***
	(0.003)	(0.003)	(0.013)
Percent Black	-0.030	-0.029	0.023
	(0.039)	(0.039)	(0.043)
Percent Hispanic	-0.119**	-0.115**	-0.027
	(0.051)	(0.051)	(0.060)
Percent American Indian	-0.190***	-0.187***	-0.190***
	(0.065)	(0.065)	(0.073)
Percent Asian	-0.834***	-0.841***	-1.687
	(0.244)	(0.244)	(1.857)
log(Median Household Income)	0.132***	0.139***	0.208***
	(0.022)	(0.023)	(0.031)
Percent Graduated College	-0.031	-0.022	-0.028
	(0.047)	(0.048)	(0.056)
Average Household Size	-0.008	-0.007	-0.035
	(0.028)	(0.028)	(0.036)
Percent Female	0.195	0.186	0.149
	(0.165)	(0.166)	(0.211)
Percent Senior	-0.031	-0.025	-0.059
	(0.100)	(0.100)	(0.122)
Percent Work from Home	-0.311***	-0.307***	-0.299***
	(0.091)	(0.091)	(0.097)
Percent Long Commute	-0.015	-0.011	-0.032
	(0.041)	(0.042)	(0.051)
Percent Rent	0.063	0.067	0.066
	(0.062)	(0.062)	(0.079)
Percent with Phone	-0.102	-0.098	-0.020
	(0.109)	(0.109)	(0.124)
Percent Rural	0.099***	0.085***	0.100**
	(0.026)	(0.030)	(0.046)
log(Population Density)	-0.033***	-0.031***	-0.035***
	(0.004)	(0.005)	(0.004)
log(Business Density)	-0.020***	-0.02***	-0.024***
	(0.006)	(0.006)	(0.007)
ψ	-	-	1.322
	-	-	(0.527)**
Instruments: Neighbors' Neighbors' Attributes	N	Y	Y
Allow for Spatial Correlation	N	N	Y
# Markets	7,642	7,642	7,642

Table 6: Entry Delay

	(1)	(2)	(3)
Entry Threat	1.128***	2.671***	3.064***
	(0.126)	(0.367)	(0.535)
Population (1,000)	-0.526***	-0.521***	-0.679***
	(0.016)	(0.016)	(0.098)
Percent Black	0.372*	0.339	0.332
	(0.217)	(0.219)	(0.294)
Percent Hispanic	2.988***	2.874***	2.428***
	(0.282)	(0.285)	(0.475)
Percent American Indian	2.565***	2.478***	2.748***
	(0.359)	(0.362)	(0.510)
Percent Asian	-0.594	-0.401	-0.323
	(1.346)	(1.358)	(4.737)
log(Median Household Income)	-1.013***	-1.172***	-1.165***
	(0.123)	(0.129)	(0.204)
Percent Graduated College	1.317***	1.079***	0.837**
	(0.257)	(0.264)	(0.411)
Average Household Size	0.213	0.188	0.246
	(0.153)	(0.154)	(0.249)
Percent Female	-2.526***	-2.304**	-0.894
	(0.912)	(0.921)	(1.566)
Percent Senior	1.761***	1.595***	2.489***
	(0.550)	(0.556)	(0.876)
Percent Work from Home	0.547	0.437	0.353
	(0.503)	(0.508)	(0.788)
Percent Long Commute	0.363	0.273	0.190
	(0.228)	(0.231)	(0.311)
Percent Rent	0.836**	0.734**	1.856***
	(0.344)	(0.347)	(0.601)
Percent with Phone	-1.388**	-1.485**	-1.217
	(0.599)	(0.604)	(0.854)
Percent Rural	-0.544***	-0.184	0.212
	(0.143)	(0.165)	(0.273)
log(Population Density)	0.795***	0.737***	0.737***
	(0.022)	(0.025)	(0.037)
log(Business Density)	0.441***	0.431***	0.432***
	(0.033)	(0.034)	(0.053)
ψ	-	-	5.679***
	-	-	(0.094)
Instruments: Neighbors' Neighbors' Attributes	N	Y	Y
Allow for Spatial Correlation	N	N	Y
# Markets	7,642	7,642	7,642

Table 7: 2013 log Maximum Available Download Speed (Mbps)

Variable	(1)	(2)	(3)
Entry Delay	0.006	-0.047*	-0.109***
	(0.006)	(0.028)	(0.030)
log(Number of ISPs)	0.863***	2.060***	1.084***
	(0.026)	(0.117)	(0.052)
Population (1,000)	0.011	-0.021*	-0.031***
	(0.006)	(0.012)	(0.012)
Percent Black	0.076	0.190	0.141
	(0.107)	(0.123)	(0.109)
Percent Hispanic	-0.280**	0.363**	-0.012
	(0.120)	(0.160)	(0.146)
Percent American Indian	-0.498***	0.570***	-0.554***
	(0.161)	(0.215)	(0.211)
Percent Asian	0.051	-0.018	0.315
	(0.590)	(0.672)	(0.475)
log(Median Household Income)	0.400***	0.137**	0.392***
	(0.052)	(0.064)	(0.062)
Percent Graduated College	0.310***	0.325**	0.288**
	(0.111)	(0.129)	(0.130)
Average Household Size	-0.081*	0.051	-0.070
	(0.042)	(0.050)	(0.048)
Percent Female	-0.036	-0.409	-0.314
	(0.225)	(0.259)	(0.259)
Percent Senior	-0.193	0.253	0.144
	(0.145)	(0.186)	(0.199)
Percent Work from Home	0.442**	0.033	0.649***
	(0.199)	(0.236)	(0.226)
Percent Long Commute	0.104	0.543***	0.065
	(0.094)	(0.115)	(0.109)
Percent Rent	-0.074	-0.054	0.107
	(0.119)	(0.140)	(0.149)
Percent with Phone	0.420	-0.037	0.696*
	(0.299)	(0.343)	(0.418)
Percent Rural	-0.216***	0.151	-0.210**
	(0.071)	(0.094)	(0.083)
log(Population Density)	0.069***	-0.009	0.170***
	(0.011)	(0.028)	(0.028)
log(Business Density)	0.009	-0.012	-0.009
	(0.009)	(0.009)	(0.008)
ψ	-	-	1.838***
	-	-	(0.002)
Instruments: Neighbors' Neighbors' Attributes	N	Y	Y
Allow for Spatial Correlation	N	N	Y
# Markets	7,642	7,642	7,642

our findings also suggest that if two identical markets have the same number of service providers today, the one which was initially entered first will have access to faster speeds. We find that each additional year of entry delay decreases present-day download speeds by 11%.

We hypothesize that this is because when facing rivals, firms are under constant pressure to upgrade the quality of their service and that absent this pressure, firms are more likely to remain stagnant. Therefore, download speeds in markets which did not exhibit this competitive pressure until recently lag behind speeds in those which developed early. In support of this, we replace $EntryDelay_{mt}$ in equation (7) with $CompetitiveDelay_{mt}$, a variable which represents the number of years from 2000 it takes for the market to become competitive.[15] We present the results of this estimation in table 8. Indeed, we find that the longer a market takes to become competitive, the slower its present-day download speed. In fact, the effect of delayed competition is stronger than the effect of delayed entry.

Initially, one might be tempted to predict the opposite result, that markets which are initially entered later are equipped with better technology and therefore would have faster download speeds today. However, 93% of zip codes had been entered by 2007, presumably with the cutting edge technology of the time. But, the prevailing download speeds of 2007 are wholly obsolete by today's standards; in fact, the average download speeds of 2007 do not even meet the FCC's current definition of broadband. Therefore, regardless of the initial technology installed, it is only through continual improvements that firms can provide the download speeds we enjoy today.

5.4 Robustness

5.4.1 Time Period

Our framework requires that we choose an initial time period, as entry delay and long-run entry must be defined relative to some base year. As our goal is to understand firms' strategies in the formative years of the industry, it was important that our base year be very early in the sample. 1999 is the earliest year in our data, but at that time, only 2% of open markets were threatened, so we chose to use 2000 as our base year.

For robustness, we also estimated all of our models using 1999 as our base year and obtained

[15] We define a market to be competitive when it has at least 4 firms.

Table 8: 2013 log Maximum Available Download Speed (Mbps)

Variable	(1)	(2)	(3)
Competitive Delay	-0.009	-0.214***	-0.133***
	(0.0008)	(0.048)	(0.045)
log(Number of ISPs)	0.861***	1.975***	1.045***
	(0.026)	(0.120)	(0.055)
Population (1,000)	0.006	-0.070*	-0.035**
	(0.006)	(0.016)	(0.015)
Percent Black	0.071	0.014	0.078
	(0.108)	(0.130)	(0.118)
Percent Hispanic	-0.264**	0.322**	-0.213
	(0.119)	(0.148)	(0.134)
Percent American Indian	-0.476***	0.625***	-0.607***
	(0.160)	(0.210)	(0.222)
Percent Asian	0.071	0.490	0.335
	(0.591)	(0.694)	(0.434)
log(Median Household Income)	0.396***	0.080	0.447***
	(0.052)	(0.066)	(0.065)
Percent Graduated College	0.313***	0.249*	0.242**
	(0.111)	(0.129)	(0.126)
Average Household Size	-0.082*	0.043	-0.056
	(0.042)	(0.051)	(0.051)
Percent Female	-0.045	-0.555**	-0.320
	(0.225)	(0.266)	(0.272)
Percent Senior	-0.164	0.418**	0.149
	(0.145)	(0.183)	(0.187)
Percent Work from Home	0.464**	0.264	0.661***
	(0.199)	(0.245)	(0.235)
Percent Long Commute	0.103	0.532***	0.086
	(0.094)	(0.117)	(0.113)
Percent Rent	-0.064	-0.037	0.104
	(0.119)	(0.139)	(0.137)
Percent with Phone	0.420	-0.061	0.755*
	(0.299)	(0.349)	(0.396)
Percent Rural	-0.226***	0.085	-0.194**
	(0.071)	(0.095)	(0.080)
log(Population Density)	0.076***	0.020	0.115***
	(0.011)	(0.023)	(0.018)
log(Business Density)	0.008	-0.022**	-0.001
	(0.007)	(0.009)	(0.008)
ψ	-	-	2.059***
	-	-	(0.002)
Instruments: Neighbors' Neighbors' Attributes	N	Y	Y
Allow for Spatial Correlation	N	N	Y
# Markets	7,642	7,642	7,642

Table 9: Key Parameter Estimates, Base Year 1999

Variable	Outcome			
	Short-run Entry	Entry Delay	Long-run Entry	Long-run Speeds
Entry Threat	-0.293***	3.997***	0.057	-
	(0.038)	(0.734)	(0.100)	-
Entry Delay	-	-	-	-0.096***
	-	-	-	(0.031)
# Markets	10,990	10,990	10,990	10,990

nearly identical results. Table 9 reports the estimates of our parameters of interest, estimated using the GMM specification which allows for spatial correlation and uses the characteristics of neighbors' neighbors as instruments.

With a base year of 1999, we find that entry threat decreases the probability of short-run entry by 0.29, and that this translates into an entry delay of 4 years. This entry delay is one year longer than what we find when using 2000 as our base year, but this is to be expected. The number of years elapsed from the base year until entry will change mechanically with the base year. We again estimate that markets which are threatened are more likely to be entered in the long run, but this estimate is not statistically significant. Finally, we estimate that one year of delayed initial entry leads to a 10% decrease in 2013 download speeds.

5.4.2 Definition of Neighbors

When defining whether two markets are neighbors, we necessarily made a choice of the maximum distance separating them. Our decision to use 3 miles was motivated by the technological constraints of the industry, but was, nonetheless, somewhat arbitrary. Therefore, we repeat our analysis using a radius of 2 and 4 miles in order to test the sensitivity of our estimates to this choice. These results are reported in table 10, estimated using the GMM specification which allows for spatial correlation and uses the characteristics of neighbors' neighbors as instruments.

Again, our results are quite robust to the neighboring markets definition and our qualitative conclusions remain unchanged. We now estimate that threatened markets receive their first entrant between 2 and 6 years later than their unthreatened counterparts, a finding which remains both statistically and economically significant. When using a 2 mile radius in our definition of neighbors, we estimate a negative effect of entry delay on long-run download speeds, but this result is not statistically significant. This is likely driven by the reduction in sample size. When requiring

Table 10: Key Parameter Estimates, Alternate Neighbor Definitions

Neighbor Radius	Variable	Outcome			
		Short-run Entry	Entry Delay	Long-run Entry	Long-run Speeds (Mbps)
2 Miles	Entry Threat	-0.257***	5.640***	0.075***	-
		(0.045)	(0.773)	(0.021)	-
	Entry Delay	-	-	-	-0.003
		-	-	-	(0.029)
	# Markets	6,110	6,110	6,110	6,110
4 Miles	Entry Threat	-0.167***	1.899***	0.080***	-
		(0.054)	(0.548)	(0.023)	-
	Entry Delay	-	-	-	-0.050**
		-	-	-	(0.025)
	# Markets	8,348	8,348	8,348	8,348

that markets be within 2 miles of one another to be considered neighbors, far fewer markets have neighbors' neighbors and our sample falls to just 6,110.

5.4.3 Excluded Markets

The validity of our instruments rests on the assumption that firms do not plan entry decisions two or more steps ahead. That is, when deciding to enter a market, they may be influenced by their desire to enter neighboring markets in the future; however, they may *not* be influenced by markets which neighbor those neighboring markets. We believe that this assumption is credible, as the industry was in its infancy and firms faced enormous uncertainty about both the industry itself and their own viability as an ISP. However, in some cases, a market and its neighbor's neighbor may be in such close proximity that our assumption is unrealistic. Therefore, we repeat the estimation while constructing our instruments using only neighbors' neighbors which are sufficiently far away from the focal market. We report results in table 11 for specifications which exclude neighbors' neighbors which are within 5 and 10 miles of the focal market. These specifications were again estimated using the GMM specification which allows for spatial correlation and uses the characteristics of neighbors' neighbors as instruments. Our results under each restriction are nearly identical to those under our previous specification, which lends credibility to the exogeneity of our instruments.[16]

[16]We also test for sensitivity by estimating specifications in which we drop observations altogether if the market is too close to either its nearest or average neighbor and obtain nearly identical results.

Table 11: Key Parameter Estimates, Excluded Neighbors' Neighbors

Required Distance	Variable	Outcome			
		Short-run Entry	Entry Delay	Long-run Entry	Long-run Speeds (Mbps)
5 Miles	Entry Threat	-0.256***	3.012***	0.088***	-
		(0.056)	(0.572)	(0.005)	-
	Entry Delay	-	-	-	-0.119***
		-	-	-	(0.026)
# Markets	7,640	7,640	7,640	7,640	
10 Miles	Entry Threat	-0.195***	2.639***	0.091***	-
		(0.052)	(0.39)	(0.005)	-
	Entry Delay	-	-	-	-0.048*
		-	-	-	(0.028)
	# Markets	5,791	5,791	5,791	5,791

6 Conclusion

There is an established literature on how incumbent firms respond to the threat of rivals' future entry. It is then natural to back up one step to ask: before entering a market, do potential entrants consider the possibility of future entry of competitors and adjust their entry strategies accordingly? If so, do potential entrants delay entry due to lowered expectation of future profits, or do they accelerate entry due to preemptive incentives? To our knowledge, Seamans (2012) is the only predecessor to our work that has explored this angle.

In this paper, we trace out the evolution of the broadband internet market, from its inception through the present. We find evidence that firms are reluctant to enter markets that are threatened by future entry of rivals. This suggests that a firm's perception of its ability to maintain market power in the future is an important factor in its entry decision. This may explain why firms at times appear to delay entry into seemingly attractive markets. We find that, on average, this strategic consideration causes firms to delay entry into open markets by three years. Although this early deployment stage is long past, this delayed entry appears to have had effects which persist even today, as markets which experienced their initial entry later have access to considerably slower download speeds.

Broadband is pivotal infrastructure to a country. Equal access to such infrastructure has been a fundamental telecommunication policy goal in the United States since the 1996 Telecommunications Act. For example, the FCC's "Connect America Fund" provides substantial subsidies to entrants into rural, insular, and high-cost areas. Our work shows that there may exist an "open market trap;" that is, even urban, seemingly prosperous markets may suffer delay and quality under-provision due to firms' strategic entry decisions. Therefore, public policy intending to encourage entry should not restrict attention to rural areas or cost considerations. Policy makers may need to factor in firms' strategic entry decisions and understand that historical rollout of internet infrastructure may have long-run impacts on important outcomes in the broadband industry.

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Appendix

Instrumental Variables First Stage Results

Table 12: Entry Threat First Stage

Average Neighbors' Neighbors' Attributes	(1)	Market Attributes	(1)
Population (1,000)	0.003***	Population (1,000)	-0.003**
	(0.001)		(0.001)
Percent Black	0.113***	Percent Black	0.012
	(0.034)		(0.030)
Percent Hispanic	0.060	Percent Hispanic	0.008
	(0.05)		(0.045)
Percent American Indian	0.150***	Percent American Indian	0.044
	(0.05)		(0.040)
Percent Asian	0.653***	Percent Asian	-0.864***
	(0.211)		(0.188)
log(Median Household Income)	0.115***	log(Median Household Income)	0.047***
	(0.016)		(0.012)
Percent Graduated College	0.025	Percent Graduated College	0.086***
	(0.034)		(0.025)
Average Household Size	0.026	Average Household Size	-0.004
	(0.019)		(0.014)
Percent Female	-0.200	Percent Female	-0.140*
	(0.124)		(0.078)
Percent Senior	0.243***	Percent Senior	0.093*
	(0.072)		(0.050)
Percent Work from Home	0.249***	Percent Work from Home	0.072
	(0.062)		(0.045)
Percent Long Commute	0.071**	Percent Long Commute	0.003
	(0.031)		(0.022)
Percent Rent	-0.077*	Percent Rent	0.075**
	(0.044)		(0.031)
Percent with Phone	0.053	Percent with Phone	0.014
	(0.076)		(0.055)
Percent Rural	-0.115***	Percent Rural	-0.155***
	(0.017)		(0.012)
log(Population Density)	0.014***	log(Population Density)	0.013***
	(0.003)		(0.002)
log(Business Density)	-0.006	log(Business Density)	0.008***
	(0.005)		(0.003)
		# Neighbors' Neighbors	0.017***
			(0.001)
# Markets	7,642		

Table 13: log(# ISPs) First Stage

Average Neighbors' Neighbors' Attributes	(1)	Market Attributes	(1)
Population (1,000)	0.004**	Population (1,000)	0.012***
	(0.002)		(0.003)
Percent Black	-0.032	Percent Black	0.029
	(0.081)		(0.070)
Percent Hispanic	-0.522***	Percent Hispanic	-0.110
	(0.109)		(0.083)
Percent American Indian	-0.294**	Percent American Indian	-0.483***
	(0.126)		(0.093)
Percent Asian	-0.373	Percent Asian	-0.010
	(0.430)		(0.329)
log(Median Household Income)	0.275***	log(Median Household Income)	0.112***
	(0.040)		(0.023)
Percent Graduated College	-0.263***	Percent Graduated College	0.052
	(0.084)		(0.053)
Average Household Size	0.158***	Average Household Size	-0.090***
	(0.046)		(0.019)
Percent Female	0.614*	Percent Female	0.238**
	(0.319)		(0.097)
Percent Senior	0.303*	Percent Senior	-0.187 ***
	(0.177)		(0.064)
Percent Work from Home	0.718***	Percent Work from Home	0.346***
	(0.158)		(0.088)
Percent Long Commute	-0.749***	Percent Long Commute	-0.225***
	(0.076)		(0.044)
Percent Rent	0.038	Percent Rent	0.038
	(0.111)		(0.053)
Percent with Phone	0.267	Percent with Phone	0.226*
	(0.185)		(0.130)
Percent Rural	-0.127***	Percent Rural	-0.288***
	(0.045)		(0.032)
log(Population Density)	0.057***	log(Population Density)	0.057***
	(0.008)		(0.006)
log(Business Density)	0.011	log(Business Density)	0.010***
	(0.012)		(0.003)
		# Neighbors' Neighbors	0.014***
			(0.002)
# Markets	7,642		

Table 14: Entry Delay First Stage

Average Neighbors' Neighbors' Attributes	(1)	Market Attributes	(1)
Population (1,000)	-0.029***	Population (1,000)	-0.331***
	(0.008)		(0.012)
Percent Black	0.493	Percent Black	0.279
	(0.377)		(0.326)
Percent Hispanic	2.272***	Percent Hispanic	-0.008
	(0.505)		(0.387)
Percent American Indian	1.563***	Percent American Indian	0.888**
	(0.584)		(0.433)
Percent Asian	1.099	Percent Asian	-1.274
	(1.994)		(1.525)
log(Median Household Income)	-0.803***	log(Median Household Income)	-0.255**
	(0.187)		(0.108)
Percent Graduated College	3.063***	Percent Graduated College	-0.277
	(0.391)		(0.247)
Average Household Size	1.136***	Average Household Size	-0.092
	(0.215)		(0.086)
Percent Female	-2.603*	Percent Female	-0.166
	(1.478)		(0.452)
Percent Senior	1.738**	Percent Senior	2.548***
	(0.819)		(0.297)
Percent Work from Home	-1.125	Percent Work from Home	1.114***
	(0.732)		(0.406)
Percent Long Commute	-0.103	Percent Long Commute	0.267
	(0.351)		(0.205)
Percent Rent	-1.111**	Percent Rent	1.144**
	(0.513)		(0.244)
Percent with Phone	0.884	Percent with Phone	-0.047
	(0.859)		(0.605)
Percent Rural	-1.586***	Percent Rural	-0.509***
	(0.208)		(0.146)
log(Population Density)	-0.322***	log(Population Density)	0.938***
	(0.039)		(0.026)
log(Business Density)	0.388***	log(Business Density)	-0.105***
	(0.055)		(0.014)
		# Neighbors' Neighbors	0.098***
			(0.010)
# Markets	7,642		

Table 15: Competitive Delay First Stage

Average Neighbors' Neighbors' Attributes	(1)	Market Attributes	(1)
Population (1,000)	-0.008	Population (1,000)	-0.296***
	(0.006)		(0.008)
Percent Black	-0.543**	Percent Black	-0.111
	(0.260)		(0.225)
Percent Hispanic	0.664*	Percent Hispanic	-0.144
	(0.349)		(0.268)
Percent American Indian	0.312	Percent American Indian	0.619**
	(0.404)		(0.299)
Percent Asian	3.811***	Percent Asian	0.477
	(1.379)		(1.055)
log(Median Household Income)	-0.824***	log(Median Household Income)	-0.273***
	(0.129)		(0.075)
Percent Graduated College	1.023***	Percent Graduated College	-0.444***
	(0.270)		(0.171)
Average Household Size	0.568***	Average Household Size	-0.031
	(0.148)		(0.059)
Percent Female	-2.711***	Percent Female	-0.735**
	(1.022)		(0.312)
Percent Senior	1.520***	Percent Senior	1.330***
	(0.567)		(0.205)
Percent Work from Home	-0.288	Percent Work from Home	0.974***
	(0.506)		(0.281)
Percent Long Commute	0.248	Percent Long Commute	0.240*
	(0.243)		(0.142)
Percent Rent	-0.646*	Percent Rent	0.258
	(0.355)		(0.169)
Percent with Phone	0.414	Percent with Phone	-0.347
	(0.594)		(0.418)
Percent Rural	-0.522***	Percent Rural	-0.163
	(0.144)		(0.101)
log(Population Density)	-0.196***	log(Population Density)	0.346***
	(0.027)		(0.018)
log(Business Density)	0.186***	log(Business Density)	-0.063***
	(0.038)		(0.010)
		# Neighbors' Neighbors	0.071***
			(0.007)
# Markets	7,642		

GMM Parameter Estimates

Table 16: Probability of Short Run Entry

Variable	(1)
Entry Threat	5.981
	(3.851)
Population (1,000)	0.2488 ***
	(0.054)
Percent Black	-1.289 ***
	(0.279)
Percent Hispanic	-1.7829 ***
	(0.371)
Percent American Indian	-2.313 ***
	(0.435)
Percent Asian	28.034 **
	(12.793)
log(Median Household Income)	0.344 ***
	(0.131)
Percent Graduated College	-0.435
	(0.349)
Average Household Size	0.081
	(0.197)
Percent Female	2.873 ***
	(0.928)
Percent Senior	0.080
	(0.643)
Percent Work from Home	1.437 **
	(0.599)
Percent Long Commute	-1.968 ***
	(0.249)
Percent Rent	0.183
	(0.402)
Percent with Phone	0.178
	(0.541)
Percent Rural	-2.362
	(1.698)
log(Population Density)	0.150 ***
	(0.032)
log(Business Density)	-0.036
	(0.035)
ψ	1.3227 ***
	(0.221)
# Markets	7,642

Table 17: Probability of Short Run Entry

Variable	(1)
Entry Threat	-1.197***
	(0.463)
Population (1,000)	0.241***
	(0.055)
Percent Black	0.080
	(0.153)
Percent Hispanic	-0.096
	(0.208)
Percent American Indian	-0.670***
	(0.255)
Percent Asian	-5.937
	(6.685)
log(Median Household Income)	0.731***
	(0.172)
Percent Graduated College	-0.099
	(0.195)
Average Household Size	-0.122
	(0.131)
Percent Female	0.524
	(0.756)
Percent Senior	-0.208
	(0.437)
Percent Work from Home	-1.052***
	(0.333)
Percent Long Commute	-0.113
	(0.185)
Percent Rent	0.233
	(0.287)
Percent with Phone	-0.070
	(0.437)
Percent Rural	0.354**
	(0.172)
log(Population Density)	-0.125***
	(0.020)
log(Business Density)	-0.084***
	(0.027)
ψ	1.322**
	(0.527)
# Markets	7,642