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Do Entry Conditions Vary over Time? Entry and Competition in the Broadband Market: 1999-2003

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February 2006

Working Paper # 06004

Department of Economics Working Papers Series

Ames, Iowa 50011

Do Entry Conditions Vary over Time?

Entry and Competition in the Broadband Market: 1999-2003*

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September 2005

Abstract

We extend Bresnahan and Reiss's (1991) model of local oligopoly to allow firm entry and exit over time. In our framework, entrants have to incur sunk costs in order to enter a market. After becoming incumbents, they disregard these entry costs in deciding whether to continue operating or to exit. We apply this framework to study market structure and competitive conduct in local markets for high-speed Internet service from 1999 to 2003. Replication of Bresnahan and Reiss's framework generates unreasonable variation in firms' competitive conduct over time. This variation disappears when entry costs are allowed. We find that once the market has one to three firms, the next entrant has little effect on competitive conduct. We also find that entry costs vary with the order of entry, especially for early entrants. Our findings highlight the importance of sunk costs in determining entry conditions and inferences about firm conduct.

JEL codes: L13 (Oligopoly and Other Imperfect Markets), L8 (Industry Studies: Services)

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1. INTRODUCTION

Economists have long held that firms' market power to set price above marginal cost is inversely related to the number of firms competing in the market. However, it has been a serious challenge to establish the number of competing firms necessary to eliminate market power. Lack of data on prices, quantities, product characteristics, and cost structures makes it difficult to separate out the demand, technologic, and strategic factors determining firms' entry, exit, and pricing decisions.

A solution proposed in a series of prominent papers by Bresnahan and Reiss (1987, 1990, and 1991) is to use entry threshold ratios to measure changes in firms' competitive conduct as the number of competing firms increases across markets. If the first entrant has monopoly power to charge a high price, it can recover fixed entry and production costs with a relatively small number of units sold or customers served. As additional firms enter, their power to set price may diminish relative to the first entrant. In this scenario, as prices fall, a larger number of units or customers served is needed in order to recover the fixed costs. A greater market size increase is then necessary to induce the second entrant than was needed to induce the first entrant. An even larger market size increase is necessary to induce the third entrant than the second, and so on. Once entry thresholds stabilize with additional entrants, one can presume that competitive pricing conditions have been satisfied.

Since its coining, the entry threshold ratio concept has become enormously influential in the field of empirical industrial organization. Subsequent researchers further developed this methodology of combining a reduced-form profit function with a game theoretic model of entry and competition.[1] However, the Bresnahan and Reiss (henceforth BR) method has some limitations that restrict its use to certain types of markets. First, the procedure is best suited to geographically distinct local service markets

[1] The main effort has been restoring differences among firms back into the model, which Bresnahan and Reiss abstract away. Berry (1992) incorporates heterogeneous potential entrants in his study of the airline market. Reiss (1996) discusses the modeling and computational issues in this type of multiple-agent qualitative response model. Toivanen and Waterson (2000, 2004) examine the UK fast food market in a Stackelberg theoretical framework. Mazzeo et al (2002, 2003, and 2004) introduce product differentiation into the BR framework in studies of motel, HMO, and telecommunication markets. Danis (2003) makes use of the identities of local exchanges in analyzing the equity option market. Seim (2004) estimates an entry model with location choices in the video retail industry.

so that researchers can clearly define market boundaries. However, mobile populations may be willing to drive a considerable distance to access some service providers such as health practitioners or auto dealers, making it difficult to pin down the exact number of firms operating in the local market. Second, researchers often find that threshold ratios vary significantly across industries, implying large differences in competitive conduct across industries.[2] While differences in sunk costs or regulatory environment across industries offer possible explanations, these large differences in threshold ratios may suggest more variation in competitive conduct than actually exists. The most important limitation is that the BR empirical framework is based on cross sectional observations of markets in equilibrium. It is not clear that the framework applies equally well to markets facing rapid entry or exit.

Using time series observations of zip-code-level local markets for providers of high-speed lines for Internet access, we seek to further the line of research initiated by Bresnahan and Reiss. The commercial provision of broadband services has expanded rapidly since 1998. Like other telecommunication industries, the competitive conduct of this thriving market has always been subject to scrutiny. This study will address the following questions: What factors encourage or deter provider entry? How many providers must exist in a market to ensure effective competition? Do entry conditions and competitive conduct vary over time? Do entry costs vary with the order of entry?

We extend the BR framework by exploiting the rich information provided by the entry and exit patterns over time. Specifically, we allow two types of firms operating in a market at any given time: entrants (who did not exist in the previous period) and incumbents (who can plan either to stay for the next period or to exit at the end of this period). We then link these firms' decisions regarding entry, continuation or exit to market size variations. New entrants, who incur sunk costs in order to enter a market, will only enter when market size has grown enough to cover their entry costs. Incumbent firms, however, do not take entry costs into consideration when deciding whether to continue operations or exit.

[2] For example, Bresnahan and Reiss (1987) show quite remarkable differences in entry threshold ratios between professional and retail industries.

This distinction allows us to identify entry costs by comparing the entry thresholds for markets which have experienced entry or exit to entry thresholds for markets experiencing no entry or exit. Estimates from our model are also able to evaluate how competitive conduct changes as the number of providers increases in a local broadband market. Temporal variation in estimated entry thresholds will help us to determine the magnitude of demand growth and/or technologic improvement in these markets and how competitive conduct changes over time.

The results of our adapted framework are striking. Results from replicating the BR framework imply that entry conditions vary dramatically over time for the 4^{th} firm entering a 1-to-3 firm oligopoly market. In particular, entry conditions become increasingly more difficult for the 4^{th} firm over time. This unreasonable variation in entry conditions disappears when the estimation accommodates entry and exit. Entry conditions for the 4^{th} firm and on are stable, implying that new firm entrants beyond the first three firms have little effect on competitive conduct. We also find that entry costs for early entrants are smaller than for later entrants, implying the existence of early mover advantages in this market. Overall, our results imply that sunk costs are a main determinant of entry thresholds. Ignoring sunk costs leads to biased measures of entry thresholds and misleading inferences about firms' competitive conduct.

The idea of using entry and exit thresholds to measure the importance of sunk costs was first used by Bresnahan and Reiss in a 1993 article published in *Annales D'Economie Et De Statistique.* They use 1980 and 1988 data on the location of rural dentists to estimate entry and exit thresholds. Finding dentists' exit thresholds well below their entry thresholds, they conclude that sunk costs play a significant role in dentists' entry decisions. While data limitations forced their empirical model to fall short of their desired fully dynamic model with forward-looking firms,[3] their paper does illustrate that sunk costs can have large effects on estimated thresholds when analyzing market entry and exit decisions. However, the

[3] Bresnahan and Reiss build a highly stylized two-period model, in which firms are forward-looking to the demand and competitive conditions in the next period. However, they only have two years of data, 1980 and 1988. In the actual estimation, they have to treat the first period as a static reduced form as they do not know the entry patterns for the first period. They also constrain the number of firms in a hypothetical third period to be the same as in 1988 because they lack data for a third period.

numerous papers that extended the BR framework to other settings have not followed the path suggested by their 1993 paper. Our study is an effort to revive that approach. Moreover, our adapted BR framework streamlines a complicated dynamic model to simplify the application and make the identification more transparent. Our results confirm that sunk costs can greatly alter the conclusions derived from the original BR estimation strategy to measure entry threshold ratios, and support the use of the dynamic extensions of the BR framework to generate accurate assessments of industry competitive environment.

The paper proceeds as follows. Section 2 recapitulates the BR framework and describes our methodology. Section 3 introduces the broadband market and the data we use. Section 4 presents empirical results for the replication of the BR model, our baseline model, and its extensions. Section 5 concludes.

2. METHODOLOGY

2.1 The Bresnahan and Reiss Framework

Bresnahan and Reiss (1991) relate shifts in market demand to changes in the equilibrium number of firms. Their method works best with personal service industries where there is a one-to-one correspondence between local population and sales. In their model, each firm's profit is defined as the difference between its variable profits and its fixed operating cost.[4] To induce one more firm to enter a market, market size as proxied by the population has to rise so that variable profits generated by the increase can cover fixed operating costs. Suppose the population must increase by s_n to support the entry of the n^{th} firm while it takes an additional s_{n+1} to support entry of the $n+1^{st}$ firm. If the fixed operating costs remain the same for all entrants, then the change from s_n to s_{n+1} tells us how quickly firms' variable profits fall as an additional firm enters. For instance, if the population increase necessary to induce entry of the 2[nd] firm is 4 times that necessary to induce entry of the 1[st] firm, then firms' variable

[4] Note that fixed operating costs are not sunk costs ---- sunk entry costs do not play a role in the static BR model.

profits and competitive conduct must have changed drastically in moving from a monopoly to a duopoly regime. Therefore, the entry threshold ratio $\frac{s_{n+1}}{s_n}$ measures the change in competitive conduct as market structure changes from n firms to $n+1$ firms. $\frac{s_{n+1}}{s_n}$ will be constant over time provided there is no change in market competitive conduct, entry and production costs change uniformly across firms, and there is no change in minimum efficient scale.[5]

The BR framework is applied to local service markets such as doctors, dentists, and pharmacists, markets with stable demand and negligible growth rates. In such cases, cross sectional variation in the number of competitors across localities will show how variation in market structure affects competitive conduct. Unclear is whether we can safely apply the BR framework to an alternative market characterized by significant entry and exit. In this study, we explore the application of the BR framework to such a market and compare the results to an adaptation of the BR framework that accommodates firm entry and exit.

2.2 Baseline Model

Ericson and Pakes (1995) propose an empirical framework of firm and industry dynamics allowing for entry, exit, firm heterogeneity, and idiosyncratic shocks. Their model requires detailed firm-level data over several time periods. Our market-level data are not sufficiently detailed to apply their framework.[6] We observe the net change of the number of firms in a local market over time, but we cannot identify individual firms or obtain any firm-specific information. By exploiting the temporal entry and

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[5] See Bresnahan and Reiss (1991) section II for how entry threshold ratios change with minimum efficient scale in a Cournot oligopoly model.

[6] Aguirregabiria and Mira (2002), Bajari and Hong (2005), Pakes, Ostrovsky, and Berry (2004) provide simplifications along this line in order to alleviate the computational burden of estimating a discrete dynamic game, but the data requirement is similar.

exit patterns of the industry, however, we can infer information about market structure and competitive conduct beyond the capabilities of the BR framework.

At any given time, a snap shot of a growing market consists of new entrants and incumbents. There is a key difference between the two firm types. When there are sunk entry costs, it takes less demand to sustain an incumbent than to support a new entrant. A firm enters the market when its expected discounted value of future profits ---- profits defined as variable profits net of fixed operating costs ---- exceeds entry costs. An incumbent firm continues operation when its expected discounted value of future profits exceeds zero, and exits the market otherwise. The purpose of the theory below is to show how firms' decisions regarding entry, continuation and exit, conditional on local demand and thus expected future profitability, will allow us to infer the magnitude of entry costs and their roles in determining entry threshold ratios.

In time period t, there are n $(0 \le n \le N)$ firms active in market m. Market demand is stochastic. At the end of each time period, all firms including potential entrants decide whether to operate in the next period based on expected market demand, technological change, and competition with other firms. In equilibrium, firms' expectations are realized. Profits differ between entrants and incumbents because entrants have to incur sunk costs to enter while incumbents do not consider these costs when deciding what to do next. This setup assumes away simultaneous entry and exit, as our market level data cannot identify that occurrence anyway.[7]

We adopt a reduced form profit function for its tractability. The n^{th} potential entrant considering entering market m with $n-1$ firms at time t has an expected discounted value of future profits of $\Pi^{E}_{n,mt} = Pop_m * \beta_t^{pop} + X_m * \beta_t - \mu_{nt} - SC_t + \varepsilon_{mt}$. After becoming an incumbent, this n^{th} firm has expected discounted value of future profits of $\Pi^{I}_{n,mt} = Pop_m * \beta_t^{pop} + X_m * \beta_t - \mu_{nt} + \varepsilon_{mt}$ if it continues

[7] We can introduce a firm-level idiosyncratic shock on profitability to account for the fact that firms simultaneously enter and exit a market. Then we can aggregate over the shocks to derive market-average firm profit. But as our data is at aggregate market level, there is no gain in our empirical investigation by doing so.

operating in market m at time t. The difference between the two profit functions is that entry costs SC_t no longer apply to incumbents.

In the above formulations, Pop_m is the population of market m, and X_m contains other market-level variables that might affect each firm's variable profits and fixed operating costs. Market size as measured by population is the key element, as in the BR study and their follow-ups. In the broadband market, plausible elements of X_m include local demographic variables such as gender, race, age and education. Local income levels, commuting patterns, and business activities are also plausible demand shifters.[8] β_t^{pop} and β_t measures how firms' time-varying expectations about a market's profitability are determined by Pop_m and X_m. For example, in 1999 a market with 1000 people might not be expected to generate sufficient demand for a single provider of high-speed lines; in 2003 the same 1000 people might be able to support two or more. Time-varying β_t^{pop} and β_t capture changes over time in consumer taste and/or technology improvements. μ_{nt} is the (expected and realized) effect on per-firm variable profits of the n^{th} firm entering the market at time t. SC_t measures the time-varying entry costs, which are sunk with the entry of the firm. SC_t, more accurately, is the difference between the actual costs of entry and the expected future sell-off values. Here we normalize the expected future sell-off values to zero. For now we assume all entrants incur the same entry costs regardless of the order of entry, but we will relax this assumption in an extension to this baseline model. ε_{mt} are market- and time-specific noises affecting firms' expected discounted value of entry or continuation, which are identically and independently distributed with: $\varepsilon_{mt} \sim N(0, \sigma_\varepsilon^2)$. The *i.i.d.* assumption about ε_{mt} will also be relaxed in an extension to this baseline model.

In the data, when we observe n firms in market m at time t, there are three situations:

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[8] Section 3 will offer a detailed discussion on the components of X_m.

1) One or more firms have entered and there were fewer than n firms at time $t-1$. For the n^{th} firm, the expected discounted value of entry exceeds zero, while for the $n+1^{st}$ firm it is negative. This can be expressed as: $\Pi^E_{n,\,mt} > 0 \quad \& \quad \Pi^E_{n+1,\,mt} < 0$.

2) No firm has entered or exited a market with n firms. All n incumbent firms from period $t-1$ have decided to stay because their expected discounted values of continuation exceed 0, while the $n+1^{st}$ firm has expected a loss from entry. That is: $\Pi^I_{n,\,mt} > 0 \quad \& \quad \Pi^E_{n+1,\,mt} < 0$.

3) One or more firms have exited and there were more than n firms at time $t-1$. The market has become unprofitable when more than n firms stayed operating. Firm-level idiosyncratic shocks decide which firms to exit. The marginal firm, the $n+1^{st}$ one, expected that it would be unprofitable to stay in the market; when this firm left, the rest of the n incumbent firms expected otherwise. That is: $\Pi^I_{n,\,mt} > 0 \quad \& \quad \Pi^I_{n+1,\,mt} < 0$.

Define N_{mt} to be the observed number of firms in market m at time t. The following econometric model can nest the above three situations:

$$
\begin{aligned}
& prob(N_{mt} = n) \\
& = \Phi(Pop_m * \beta_t^{pop} + X_m * \beta_t - \mu_{nt} - SC_t * I[entry_{mt}]) \\
& \quad - \Phi(Pop_m * \beta_t^{pop} + X_m * \beta_t - \mu_{n+1,\,t} - SC_t * I[entry_{mt}] - SC_t * I[Incumbent_{mt}]) \\
& = f(X_m,\, I[entry_{mt}],\, I[Incumbent_{mt}];\, \theta),
\end{aligned}
$$

where $I[entry_{mt}]$ and $I[Incumbent_{mt}]$ are indicator functions. The definitions of these two indicator functions are:

$I[entry_{mt}] = 1$ if market m had less than n firms at time $t-1$; $I[entry_{mt}] = 0$ otherwise.

$I[Incumbent_{mt}] = 1$ if market m had n firms at time $t-1$; $I[Incumbent_{mt}] = 0$ otherwise.

In the above econometric model, the parameter vector is $\theta = [\beta_t^{pop}, \beta_t, \mu_{nt}, SC_t]$.[9] We then employ maximum likelihood methods to estimate this parameter vector:

$$\begin{aligned}\hat{\theta} &= \arg\max \sum_{m=1,\ldots,M} \ln(prob(N_{mt} = n)) \\ &= \arg\max \sum_{m=1,\ldots,M} \ln(f(Pop_m, X_m, I[entry_{mt}], I[Incumbent_{mt}]; \theta)).\end{aligned}$$

Define S_{nt} to be the necessary population to support the total of n firms in a local market at time t. Also define s_{nt} to be the necessary population to support the entry of the n^{th} firm. With the estimates $\hat{\theta}$ and the entrants' expected payoff function, we can calculate S_{nt} by $S_{nt} = \dfrac{\widehat{\mu_{nt}} + \widehat{SC_t} - \overline{X_m} * \widehat{\beta_t}}{\widehat{\beta_t^{pop}}}$, where $\overline{X_m}$ is the cross-market average of X_m. Naturally, we calculate entry threshold for the n^{th} firm by $s_{nt} = S_{nt} / n$, and entry threshold ratios from n to $n+1$ firms by $\dfrac{s_{n+1,t}}{s_{nt}} = \dfrac{S_{n+1,t}/(n+1)}{S_{nt}/n}$.

The BR framework is a special case of our 3-case scenario. In the markets BR studied, all firms are incumbents in an equilibrium market structure, and so case 2 in isolation can be viewed as the BR framework:

$$\begin{aligned}&prob(\Pi_{n,mt}^{I} > 0 \quad \& \quad \Pi_{n+1,mt}^{E} < 0) \\ &= \Phi(Pop_m * \beta_t^{pop} + X_m * \beta_t - \mu_{nt}) - \Phi(Pop_m * \beta_t^{pop} + X_m * \beta_t - \mu_{n+1,t} - SC_t)\end{aligned}.$$

Even if the BR model admits entry costs, it cannot distinguish SC_t from $\mu_{n+1,t}$ because there are no measures of entry costs.[10]

In contrast, our model allows identification of the entry costs without relying on explicit measures of entry costs. The identification comes from the variation in entry and exit patterns across markets and

---

[9] The variance of ε_{mt}, σ_{ε}^{2}, is normalized to unity as is typical when the dependant variable is discrete. We also normalize the constant term in $X_m * \beta_t$ to be zero as it is not identified from the cutoff points μ_{nt}.

[10] Bresnahan and Reiss (1991) have some market-level measures of fixed operating costs, but these are not the same as entry costs.

across time. As shown in Figure 1, the distances from μ_{nt} to $\mu_{nt}+SC_t$, from $\mu_{nt}+SC_t$ to $\mu_{n+1,t}$, and from $\mu_{n+1,t}$ to $\mu_{n+1,t}+SC_t$, are now estimable by comparing the demand thresholds inducing the n^{th} firm to enter, forcing the $n+1^{st}$ firm to exit, and sustaining n firms to stay.

It is useful to offer a broader interpretation on how sunk costs will affect firm strategic entry decisions. In the most straightforward way, sunk costs are "necessary" investment costs for entrants to start businesses. However, there are at least two other potential components of sunk costs. First, incumbents' strategic behavior, e.g. preemption and entry barriers, may lower the entrants' expected discounted future profits. In this situation, potential entrants will delay entry as if there were higher sunk costs to enter.[11] Second, the costs consumers face in switching from incumbents to the new entrant, which are especially important in telecommunication industries, may also create disadvantages for later entrants. These disadvantages will, again, delay entry as if there were higher sunk costs for later entrants. We cannot distinguish between these different types of sunk costs empirically, but our framework will be able to measure whether there is a difference in expected profitability between entrants and incumbents consistent with the potential differences in sunk costs faced by early and late entrants.

2.3 Extension 1: Allow Entry Costs to Vary With the Order of Entry

As just discussed, we are not able to exactly distinguish between the "necessary" and the "strategic" sunk costs. However, we can allow entry costs to vary with the order of entry in the hope of capturing the differences in sunk costs between early and later entrants. The expected discounted value of future payoffs for the n^{th} firm entering market m at time t is now $\Pi^{E}_{n,mt} = Pop_m * \beta^{pop}_t + X_m * \beta_t - \mu_{nt} - SC_{nt} + \varepsilon_{mt}$. Note that entry costs vary with the order of entry, as embodied by subscript n in SC_{nt}. Accordingly, we have:

[11] Baumol et al. (1982) point out that "the need to sink costs can be a barrier to entry" because incumbents may subject entrants to higher expected cost. For a review on strategic models of entry deterrence, see Wilson (1990).

$$
\begin{aligned}
&prob(N_{mt} = n) \\
&= \Phi(Pop_m * \beta_t^{pop} + X_m * \beta_t - \mu_{n,t} - SC_{nt} * I[entry_{mt}]) \\
&\quad - \Phi(Pop_m * \beta_t^{pop} + X_m * \beta_t - \mu_{n+1,\,t} - SC_{n+1,\,t} I[entry_{mt}] - SC_{n+1,\,t} * I[Incumbent_{mt}])
\end{aligned}
$$

2.4 Extension 2: Incorporate Market Random Effects

In our baseline model, we estimate the parameters period by period, allowing them to vary with time. While this allows firms' expected discounted values of future payoffs to be flexibly determined,[12] we lose the ability to control for unmeasured market-level heterogeneity, which may be an important factor determining entry and exit. A potential solution is to estimate a market random effects model, while the market can be at county level. That is, we introduce a market-specific error term in the profit functions. For example, firms offering services in the same country may be subject to a county-specific shock. Thus a modification of our baseline model is:

$$\Pi_{n,mt}^{E} = Pop_m * \beta_t^{pop} + X_m * \beta_t - \mu_{nt} - SC_t + \eta_{county} + \varepsilon_{mt}$$

$$\Pi_{n,mt}^{I} = Pop_m * \beta_t^{pop} + X_m * \beta_t - \mu_{nt} + \eta_{county} + \varepsilon_{mt}\,.$$

η_{county} is a time-invariant mean zero error with:

$$
\begin{aligned}
&\operatorname{cov}[\eta_{county\_i}, \eta_{county\_j} \mid X_m] \\
&= \operatorname{var}[\eta_{county} \mid X_m] = \sigma_{county}^2 \quad \textit{if} \quad county\_i = county\_j; \\
&= 0 \qquad\qquad\qquad\qquad \textit{otherwise.}
\end{aligned}
$$

Estimation of this model involves greater computational burden than the baseline model because the likelihood function involves integration over the market random effects η_{county}. We use the method of simulated maximum likelihood to estimate this model.

[12] A less flexible way is to force β to be the same for all time periods and use time dummies to pick up demand fluctuations.

3. THE BROADBAND MARKET AND THE DATA

3.1 The Broadband Market

Privatization of the Internet in 1994 opened the door to its commercial use and to competition among Internet service providers. Over the decade since, the market for providers of high-speed lines has grown rapidly. The number of high-speed lines increased 10 fold from 2.8 million in December 1999 to 28.2 million in December 2003, the sample for which we have data.[13] The vast majority of these lines served residential and small business subscribers.[14] This sample period dates back almost to the birth of the market. The FCC (2000) estimates that only 0.3% of households had broadband service in 1998. By the end of 2003, 21% of U.S. households had broadband access. The total number of providers of high-speed lines has increased from 105 in December 1999 to 432 in December 2003. By December 2003, 93% of zip codes encompassing 99% of the country's population had at least one provider of high-speed lines, compared to 60% of zip codes in December 1999. Clearly, the market structure for the broadband industry was evolving rapidly.

Providers of high-speed lines provide broadband services by means of several mutually exclusive types of technology. The two major types are asymmetric digital subscriber lines (DSL)[15] and cable modems using hybrid fiber-coaxial cable networks, operated primarily by cable television operators.[16] As of December 2003, coaxial cable has accounted for 58.3% of all high-speed lines, while DSL has accounted for 33.7%. Cable television companies, incumbent local telephone companies (incumbent local exchange carriers, or ILECs), and new entrants into telecommunications services (competitive local exchange carriers, or CLECs) compete for subscription. Recent rapid technological changes have led to a sharp decline in the cost of cable and DSL service. Monthly prices were $27 in many areas in 2004, down

[13] FCC (2004) reports most of the statistics we refer to in this section.
[14] 1.8 million high-speed lines served residential and small business subscribers as of December 1999 and 26 millions lines did so as of December 2003.
[15] Asymmetric DSL provide speeds in one direction greater than speeds in the other direction.
[16] Other technologies include: wireline technologies "other" than ADSL, including traditional telephone company high-speed services and symmetric DSL services; optical fiber to the subscriber's premises; and satellite and terrestrial wireless systems, which use radio spectrum to communicate with a radio transmitter.

from $40 in 2003. Again, the record on prices and technology suggests that the market is characterized by rapid changes.

While many other governments, most notably Korea, are investing heavily in broadband, the United States has left broadband investment mostly to private companies. In recent years, the U.S. government's broadband strategy is to foster competition by reducing regulatory hurdles. The idea is to encourage entry and competition, which will lower prices and boost broadband use. Whether this strategy works or not boils down to examining entry conditions faced by different firms in different times, the focus of this study.

3.2 Market Definition

In order to determine entry thresholds for providers of high-speed lines, we must first define the local market. The definition hinges on the mobility of consumers' demand. An important advantage of the broadband market is that consumers' demand is certainly local ---- consumers can only order services from providers which offer service in their neighborhood. Consequently, we do not face the problem common to market structure studies that customers can travel from one market to another, blurring the geographic boundaries of a market.

Our definition of a local market also reflects the type of entry decision on which we focus. In this application, we are not concerned with the decision of whether to enter or exit the broadband service market more generally, but only on the marginal decision of whether an already existing provider will serve one more local market. Our definition of the geographic boundaries of the market will reflect the sunk costs associated with this marginal market entry decision. For example, if the sunk costs of serving a new area were confined to local TV and newspaper advertising, we would define the local markets by county or city boundaries that reflect the boundaries of the local mass media market.

The best definition of a local geographic market for our study is a zip code tabulation area, as defined by the 2000 Census of Population. The marginal decision of whether or not to serve one more area involves sunk costs that are mostly committed at the zip code level, particularly in the less densely populated areas that we focus on in this study. These costs involve application of the so-called "last mile" technology that connects the switching and distribution centers of local telecommunications and cable television companies to the home users of broadband services. Basically, providers of high-speed lines are data transporters in this "last mile" of the network. For DSL services data passes over part of the spectrum on copper telephone wires; for cable services data pass over part of the spectrum on the coaxial cable that distributes cable television. Because both services are offered over networks designed for other services, the providers must make substantial investments in renovation before serving an area. Sunk costs of serving an additional area are mainly composed of the renovation costs of the existing networks and the costs of building switching and distribution centers (Jackson, 2002). The distance between the user's premises and a phone company's central office or cable installation is a primary factor in deciding which neighborhoods to serve and the speed of these services. DSL is typically available within a radius of 3.5 miles from the central office,[17] while cable modem service areas are larger. Based on the 2000 population Census, a typical zip code covers a radius of 3 to 4 miles, roughly consistent with the area that could be covered by a DSL system. Other possible geographic boundaries such as cities, counties, or MSAs are too large relative to a broadband service area, and could include providers that do not actually compete with each other. This makes zip code areas the finest approximation of local markets in the broadband market.[18]

Above said, we still need to be cautious in dealing with different types of firms and their potentially different sunk costs. The 1996 Telecommunications Act and other FCC regulations allow

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[17] For example, San Francisco has 24 zip code areas and 12 central offices, none of which are more than four miles from each other (Prieger, 2003).

[18] Augereau, Greenstein, and Rysman (2004) take local calling areas as distinct markets to study Internet service providers' adoption of different technology standards for 56K modems. In their study, a provider's technology adoption decisions do not vary with zip codes. However, in our study each zip code may have a distinctive set of competitors.

CLECs to use ILECs' infrastructure based on the total-element, long-run, incremental cost. Most CLECs choose exercising this option over investing in their own network infrastructure and spend large sums of money on marketing. This creates a distinction between the sunk costs of CLECs and those of ILECs and makes the extension of our baseline model a more meaningful exercise.[19]

We do not focus on the overall decision of whether a given provider enters, remains in, or exits business because market distinctions blur. Almost all providers serve multiple areas. A few have national or near-national footprints,[20] more offer services beyond one city, and hundreds of small providers only cover a small geographic area. Different sized providers will differ in their business strategies regarding the scale of geographic markets to cover. Markets defined by the overall broadband entry decision will overlap, leading to a variety of competitive interactions. Any two providers might compete with one another in some geographic areas and not in the others. Without firm identities and firm-specific coverage area in our data, the problem of overlapping markets would be insurmountable if we chose to investigate providers' entry decisions at the firm level.

3.3 The Data

Our primary data set is the Survey of High Speed Internet Providers, conducted every six months by the National Telecommunications and Information Administration since December 1999. The surveys report the number of providers for each zip code in the United States. The Federal Communications Commission (FCC) requires every facilities-based provider with at least 250 high-speed lines to report basic information about its service offerings and end users twice a year to the Commission.[21] Each provider is required to report its presence in a given zip code as long as it serves at least one customer in

[19] In the extension, we allow sunk costs to vary with the order of entry. If CLECs tend to enter after ILECs in the broadband market, which is usually true, this extension will capture the differences in sunk costs between these two different types of firms.
[20] For example, Time-Warner America Online.
[21] High-speed lines are defined as those that provide speeds exceeding 200 kilobits per second (kbps) in at least one direction.

that zip code. The FCC then releases summary statistics to the public aggregated to the zip code level, which provides us 9 snapshots of the number of firms competing in each broadband market. Figure 2 shows that the number of high-speed Internet service providers varies substantially over time, across states, and across communities within states.

The data set is close to "ideal".[22] First, the providers of high-speed lines market is growing rapidly and there is significant entry and exit during the time span of the data. Second, we have a cleaner definition of markets than in most of the previous entry studies. The data tell us exactly how many firms are competing within a zip code. Because consumers cannot order Internet services from providers not servicing their home market, the zip code market boundary is exact.

The data has several drawbacks, however. We do not know the identities of the firms, so we can only observe net instead of actual entry and exit. It is likely that high-speed Internet services are correlated across adjacent zip codes as most providers serve more than a single zip code, but we have no way to deal with this potential correlation.[23] Furthermore, cable and DSL are different products that are not perfect substitutes, but we are unable to distinguish between them. Mitigating this problem is the similarity in cost and structure for DSL and cable modems (Jackson, 2002).[24] Small providers, many of which serve sparsely populated areas, are not required to report to FCC, potentially causing measurement errors in our econometric analysis.[25] Again fortunately, few providers would fall into this category. Research shows that entry will not pay off unless there are at least 200 lines in a DSL service area (Paradyne, 2000). The most serious drawback is that the FCC summary data by zip code does not distinguish between 1, 2 or 3 providers to avoid violating confidentiality. This prevents us from studying the change of competitive conduct from the 1st to the 3rd provider.

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[22] Citing Bresnahan and Reiss (1991), "ideally, we would like to observe a single industry in which market demand has fluctuated enough to cause significant firm turnover."

[23] However, these correlations do not affect the consistency of our estimates (need elaboration).

[24] Jackson (2002) compares the costs of cable versus DSL from all aspects: 1) the cost of modems; 2) the cost of connecting to the aggregated traffic; 3) the cost of the transmission plants; 4) the cost of the DSL's central office and the cable system's head end; 5) the cost of marketing, installation, and customer support. He concludes that the costs only differ slightly across the two platforms.

[25] Small providers (with less than 250 high-speed lines) may provide information on a voluntary basis.

To complement the main data, we merge in information from the 2000 Population Census based on zip code tabulation areas (ZCTAs).[26] Our measure of market size is the population in ZCTAs. In addition, we use average income, education, age, ethnicity, commuting distance, population density etc. as factors affecting local demand for and/or the cost of providing high-speed Internet services. The zip code data are also matched to the Federal Information Processing Standards (FIPS) codes, which allow us to merge in the number of firms per thousand in the county population in 1998. We use this variable from the Bureau of Economic Analysis as a proxy for local business activities.

3.4 Sample Selection and Summary Statistics

While zip code areas provide a good geographic definition for our broadband markets, we need to further refine our market definition to ensure: 1) measurement errors in the data are minimized; 2) a market covers a large enough geographic area so that sunk costs must be committed to enter; 3) all providers in a market are able to compete with each other. To satisfy these conditions, we select a sample from the universe of 31913 zip codes in the United States.[27] We first sort the data by population density. We drop the bottom 5 percent, which corresponds to very sparsely populated rural areas, where the measurement error problem is more severe (see section 3.3). We also drop the top 5 percent, which corresponds to metropolitan areas (e.g. San Francisco, New York City) where zip codes may not provide a sufficiently large area.[28] For the rest of the zip code areas, we opt for zip codes with populations below the median (roughly 2750) to focus on markets that would be more prone toward an oligopoly structure. Furthermore, a zip code with populations above the median covers a much larger geographic area and we

[26] ZCTAs, defined by the Census Bureau, are not identical to zip codes, defined by the U.S. postal service. However, all the zip codes from the FCC data do have a match in the 2000 Census data.
[27] We do not include Puerto Rico zip codes in the universe of the zip codes. We also delete zip code areas with "HH" or "XX" as the last two digits. They are specially coded by the Census Bureau to cover large water areas or rural areas with few people (e.g. parks, forest lands, desert, and mountainous areas).
[28] A typical zip code area in this category covers a radius less than 1 mile.

are concerned that providers serving such a zip code did not compete with each other.[29] Our selection criteria leave us with 14364 zip codes observations per period over 9 semi-annual time periods from December 1999 to December 2003.[30]

Table 1 reports summary statistics on the average number of providers and the proportion of zip codes experiencing net entry or no net change. As shown here, the number of providers in a zip code area has increased monotonically over time. In December 1999, these markets averaged only 0.27 providers per market. Four years later, they averaged 1.09 providers per market. There is tremendous variation in the distribution of providers. In December 1999, 74% had no providers while others had as many as 9. Four years later, 27% had no providers while other markets had as many as 17. Entry and incumbency occurred steadily over the nine periods except for a surge of entry during December 2000 and June 2001. In every 6 month time period, around 10% of the zip codes added at least one more net provider. Around 85% had no net change in providers, leaving the residual 5% losing at least one provider.

Table 2 reports the proportion of zip codes with various numbers of providers in each of the periods. There was considerable entry over the four years. Almost 50% of the zip codes experienced a first entrant during the period. The most significant growth was in the 1 to 3 provider category, with the share of zip codes in that group rising from 26% to 64% over the period.

Table 3 describes demographic variables previously identified by Prieger (2003) as relevant to market profitability. On average, our zip code markets have a population of 1018 with a land area of 53 square miles.[31] The vast majority are White, with 5% African American, 4% Hispanic, 2% Native American, and 0.4% Asian. Median household income average $35 thousand with 38% percent of the population having had at least some college education. One-third of the population is over 60. Around 5%

[29] We can show that there is strong positive correlation between population residing in a ZCTA and the area size of this ZCTA when metropolitan ZCTAs are dropped from the sample.

[30] We have tried some different cutoff points in all steps of selecting the sample (specifically, dropping the top and bottom 10% based on population density and/or dropping zip codes with populations below [2500, 4000]). The results are similar.

[31] The population density is 189 per square mile on average. Note, the population density is a non-linear function of population and land area, therefore the mean of the population density is different from the mean of population divided by the mean of land area.

of the working population work at home, while around 20% have to spend more than 40 minutes commuting to work. Around 20% of households rent, and the vast majority (96%) have a telephone at home. Because of our sample selection criteria, 92 % of the population is rural. On average, there are 24 firms per thousand in the population.

4. RESULTS

A closer look at the data can give us an idea why the static BR framework cannot be applied to an industry with significant growth. Table 4 reports the percentage of all the zip codes with n firms that experienced net entry or no net change over each 6 month period under study. As of June 2000, 31.7% of the markets with 1 to 3 providers gained at least one provider. The percentage decreases over time so that by December 2003, only 7.5% of the markets with 1 to 3 firms had experienced net entry over the previous six months. The rest of the categories display a similar pattern, but the change over time is much smaller. This suggests that entry into the 1 to 3 provider category happens much earlier than entry into other categories. While markets with $n > 4$ providers still experience significant entry at the end of the time period, markets with 1 to 3 providers are composed mostly of incumbents. In that group, 91% experienced no net entry or exit in the six-month period ending in December 2003. Without considering the sunk costs which only entrants have to incur, the BR framework will generate a weighted average of the "true" entry threshold and a smaller, "incumbency" threshold----the market size that allows the n^{th} incumbent firm to remain in business. Therefore, the BR replication results will underestimate entry thresholds for all categories, with the bias most significant for the category with 1-3 firms toward the end of our survey period when incumbents dominate the sample. We conjecture that the BR framework will overestimate the entry threshold ratios most for $\frac{s_4}{s_{1-3}}$, especially in the later periods as incumbency dominates.

4.1 Replication of the Bresnahan and Reiss Framework

Table 5 reports estimates from the ordered Probit model using the BR framework. Note for each regression a normalization of the variance of the error term has been made so we cannot compare coefficients across time periods. The vast majority of coefficient estimates are as one would hypothesize about factors that shift profitability in the broadband market. Population size is a significant determinant of the number of providers operating in a zip code. Zip codes with a higher percentage of Hispanics and Native Americans discourage the presence of broadband providers, while a higher percentage of Asians raises the number of providers. Evidence of the impact of Black populations is mixed. Richer and better-educated populations attract more providers, while zip codes with larger households,[32] more females, and more senior citizens discourage them. Populations that rent, have a telephone at home, work at home, or have longer commuting distances attract broadband services. Rural areas attract fewer providers, while areas with more prosperous businesses activity, as measured by firm density, attract more. All these coefficients are stable over time and most of them are statistically significant. The only puzzle is that population density lowers the number of providers as one would think that the cost of providing Internet services should be lower in more densely-populated areas.

In table 5, the cutoff points μ_{nt} are estimated with very good precision. Table 6a and 6b are calculated based on the estimates of the coefficients and cutoff points in table 5. Table 6a reports the absolute entry thresholds derived from $S_{nt} = \dfrac{\widehat{\mu_{nt}} - \overline{X_m} * \widehat{\beta_t}}{\widehat{\beta_t^{pop}}}$. The entry threshold indicates the market size necessary to support n firms at time t, as measured by population size in thousands. Note that these thresholds are comparable across time periods because they are defined as ratios of coefficients, and so the units cancel out. As time goes by, less population is necessary to support a given number of providers. As shown in the table, around 2,400 people are necessary for a zip code area to support 1 to 3 providers in

[32] People in the same household usually share one broadband provider so larger households reduce effective demand.

December 1999, while only 186 people are necessary in December 2003. Similarly, around 7,100 people are necessary to support 4 providers in December 1999 but only 2800 in December 2003. The rapid reduction in the number of people necessary to support a given number of providers suggests either that broadband demand is growing rapidly over the four years, that technology is rapidly lowering production cost, or both.

Table 6b reports the entry threshold ratios calculated from $\frac{s_{n+1,t}}{s_{nt}} = \frac{S_{n+1,t}/(n+1)}{S_{nt}/n}$. They are also comparable across time periods. As discussed earlier, when $\frac{s_{n+1,t}}{s_{nt}} = 1$, there is no change in competitive conduct in moving from n to $n+1$ firms in the zip code area.

Recall that our data cannot distinguish whether there are 1, 2, or 3 providers in a given zip code. As a result, S_{1-3} is a function of s_1, s_2, and s_3, and we cannot directly estimate $\frac{s_4}{s_1}$ or $\frac{s_4}{s_3}$. We could report $\frac{s_4}{s_1} = \frac{S_4/4}{S_{1-3}}$, which underestimates $\frac{s_4}{s_1}$, or report $\frac{s_4}{s_3} = \frac{S_4/4}{S_{1-3}/3}$, which overestimates $\frac{s_4}{s_3}$.[33] Instead, we generate a measure that lies between the two extremes. We assume that there is no change in competitive conduct in moving from a monopoly market to a 3-firm market, i.e., we assume $s_1 = s_2 = s_3$. Under that assumption, $S_{1-3} = s_1 * P_1 + 2s_2 * P_2 + 3s_3 * P_3 = s_1 * (P_1 + 2P_2 + 3P_3)$, where P_n is the percentage of providers in the n^{th} category ($n = 1, 2, or\ 3$) among all 1 to 3 firm oligopoly market. The FCC does report the distribution of 1-, 2- and 3-provider markets at the national level for every period, and we use this distribution data as our measures of P_1, P_2, and P_3. Given that approximation, we define $\frac{s_4}{s_{1-3}} revised = \frac{S_4/4}{s_1} = \frac{S_4/4}{S_{1-3}/(P_1 + 2P_2 + 3P_3)}$. $\frac{s_4}{s_{1-3}} revised$ will also underestimate $\frac{s_4}{s_1}$ and

[33] This is because $s_1 \le S_{1-3} \le 3 * s_3$.

overestimate $\frac{s_4}{s_3}$ because $s_1 \leq s_2 \leq s_3$, but the bias will be smaller. Alternatively, we can interpret $\frac{s_4}{s_{1-3}}\ revised$ as measuring the average change in competitive conduct when the 4th firm enters a 1-3 firm oligopoly market.[34]

As shown in table 6b, when $n > 4$, $\frac{s_{n+1,t}}{s_{nt}}$ are close to unity with only slight increases over time, suggesting that competitive conduct is stable when market structure goes beyond 4 firms. There are huge variations over time for $\frac{s_4}{s_{1-3}}$ and $\frac{s_4}{s_{1-3}}\ revised$. For both, the threshold ratios rise over time, suggesting that entry into a 1-3 firm oligopoly market gets progressively more difficult over time. Using the revised measures, whereas in December 1999, competitive conduct seems not to change appreciably as the 4th firm is added, by December 2001 it takes nearly twice the 1-3 firm market size to support the 4th entrant, and by December 2003, it takes around 7.5 times the market size. A similar pattern occurs with the unrevised measure that is subject to greater downward bias. The implication is that firms are finding it increasingly difficult to enter the broadband markets with less than four incumbent firms.

4.2 Results of Our Baseline Model

The construction of table 7, 8a, and 8b is the same as table 5, 6a, and 6b. Table 7 reports MLE results from our baseline model; table 8a reports entry thresholds measured in population; table 8b reports entry threshold ratios. Comparing table 7 and table 5, we can see that the coefficient estimates for the control variables are very close. The estimated effect of population on the number of providers steadily increases over time in table 7, but the increase is modest in magnitude compared to the much more rapid increase in table 5. We suspect that this is because the population coefficient absorbs some of the ignored

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[34] We sometimes omit the t subscript following s_n, when n takes a number, to simplify notion.

effects of entry costs in the BR framework. Because of the normalizations we employ for every time period, we are not able to further investigate this conjecture.

Though the coefficients between table 5 and table 7 are not comparable due to the normalizations we have made, there are two major differences worthy of our attention. First, the cutoff points μ_{nt} in table 7 are much smaller in magnitude. Second, in table 7 entry cost SC_t is estimated. Both μ_{nt} and SC_t are precisely estimated. Their combined magnitudes roughly match the magnitudes of the estimates of μ_{nt} in table 5.

As we discussed earlier, we expected that the BR framework would underestimate entry thresholds by ignoring entry costs, especially for entry into the 1-3 firm category and that the bias would increase later in the period as incumbents increased in proportion to the total number of firms. Table 8a confirms our predictions. Every threshold reported here is larger than its counterpart in table 6a. By December 1999, the population necessary to support a 1-3 firm oligopoly was 3,606, while the BR estimate was 2,420; by December 2003, the population necessary to support the same market structure was 2,024 rather than 186 as implied by the BR estimate. These patterns are the same for all other market structures. In other words, the BR framework generates a downward bias in estimating entry thresholds. Figure 3 is a graphical illustration of this bias, which can be measured by the gap between the solid and dotted line for the same market structure category. For clarity we only show estimates for $n = 1-3$ and $n = 4$. We can see that the bias falls in June 2001 when there was a surge of entry. Then the bias jumps in magnitude in December 2001 when new firm entry dropped and the incumbent share rose sharply. The bias is especially large for $n = 1-3$ in later periods, exactly as we have conjectured.

Equally dramatic changes occur in the threshold ratios reported in table 8b. Although results for $\frac{s_5}{s_4}$, $\frac{s_7}{s_6}$ and $\frac{s_6}{s_5}$ are essentially unchanged, the pattern of dramatic increases in $\frac{s_4}{s_1}$ and

$\frac{s_4}{s_{1-3}}$ *revised* found in table 6b is no longer obtained. There are small rising deviations from unity for $\frac{s_4}{s_{1-3}}$ *revised* , hinting that the competitive conduct from a 1-3 firm oligopoly to a 4-firm market indeed changed slightly over time (for a comparison of the BR replication results and our baseline model' results see figure 4). However, because $\frac{s_4}{s_{1-3}}$ *revised* is an overestimate of $\frac{s_4}{s_3}$ and is theoretically bounded above unity, there seems to be no change of the entry conditions for the 4th entrant from a 3-firm market structure. Therefore, though we are not able to infer the competitive conduct change inside the 1-to-3 firm category due to data limitations, we are safe to conclude that the fringe players from the 4th firm on have little effect on the competitive conduct of the broadband market.

In table 9, we test formally for systematic differences in entry threshold ratios over time. We use likelihood ratio tests to examine whether entry threshold ratios remain unchanged from period $t-1$ to t. To perform the test for the null hypothesis $\frac{s_{nt}}{s_{n-1,\,t}} = \frac{s_{n,\,t-1}}{s_{n-1,\,t-1}}$, we constrain μ_{nt} to be a function of other coefficients and obtain the new log likelihood under the constraint. There is a statistically significant change over time in competitive conduct from a 1-3 firm oligopoly to a 4-firm market. Moreover, this change shows some, if not huge, economical significance as shown in table 8b, implying the entry conditions for the 4th firm has indeed changed somewhat over the fours years of our observation. Furthermore, in June 2003 the change from last period is statistically significant for every category, showing that the period from December 2002 and June 2003 displays more conduct change than any other period.

4.3 *Do Entry Costs Vary with the Order of Entry?*

Table 10a and 10b reports results from the first extension of our baseline model, which allows entry costs to vary with the order of entry. Table 10c reports likelihood ratio tests for the null hypotheses $SC_{1-3,t} = SC_{4t} = SC_{5t} = SC_{6t} = SC_{7t}$ and $SC_{1-3,t} \neq SC_{4t} = SC_{5t} = SC_{6t} = SC_{7t}$. Our baseline model is the most restrictive model. In table 10a, we allow the sunk costs of entrants into the 1-3 firm oligopoly market to be different from the later entrants. In table 10b, we allow the sunk costs of the 4th entrant to be different as well. As most coefficient estimates are very close to the baseline model, we only report estimates for the entry costs SC_{nt}. The pattern of estimates in both tables is that sunk entry costs into the 1-3 firm oligopoly market are smaller than for later entrants, but only for the early time periods. Furthermore, table 10c shows that we can reject the null hypotheses $SC_{1-3,t} = SC_{4t} = SC_{5t} = SC_{6t} = SC_{7t}$ but cannot reject $SC_{1-3,t} \neq SC_{4t} = SC_{5t} = SC_{6t} = SC_{7t}$ for these early periods. These test results support the findings in table 10a and 10b, i.e. in early broadband market the entrants into the 1- to 3- firm oligopoly market has distinctively different entry costs than the later entrants. As Greenstein (2000) argues, many small and medium providers took strategic positions as early movers into new technology and new services as a way to develop local customer bases and differentiate from their branded national rivals. Our evidences support his argument: early mover advantages seem to discount entry costs for early entrants into the broadband market, or put it another way, increase the "strategic" entry costs for later entrants.

4.4 *How Important is County-specific Heterogeneity?*

Table 11a, 11b, and 11c reports results from the second extension of our baseline model, which allows county-level random effects. As table 11a shows, the variance of the country-specific error η_{county} is estimated with high precision. Comparing table 7 and table 11a, we can see that controlling for random effects greatly improves the log likelihood. Though table 11a suggests the importance of allowing profitability of adjacent markets to be correlated, table 11b and 11c suggests otherwise. In table 11b and 11c, the estimated entry thresholds and entry threshold ratios only change very little from table 8a and 8b. In fact, all the structural parameters and their variances are very closely estimated with or without county-level random effects. This is not surprising: our baseline model already produces consistent estimators and the random effects model can only improve efficiency. With our large sample of zip codes, the baseline model is already estimated with good precision. If the sample size is small and parameters are less precisely estimated, we suspect that incorporating market random effects might play a more significant role. The relative ease with which market-level heterogeneity can be incorporated into our adapted BR framework will help in future investigations of markets structures that have more limited samples.

5. CONCLUSIONS

In this paper we incorporate sunk costs into an empirical framework estimating a discrete game of firm entry and exit. Application of our framework to a fast evolving market ---- the broadband market from 1999 to 2003 ---- displays a drastically different picture from the one well established in the literature. The huge variations in the changes of competitive conduct when the 4^{th} firm enters exist only as an artifact of disregarding entry and exit in the empirical framework. Our results show that there are only small variations of entry threshold ratios. Once the market has between one to three firms, the next entrant has little effect on competitive conduct in the local broadband market. Our work highlights the importance of sunk costs in determining entry conditions and inferences about firm conduct.

An immediate next step to this paper should allow for entrants' expectation of the evolution of future market structure. For example, firms may have a greater incentive to be among the first set of entrants if they expect that the market will support a stable oligopoly market structure rather than inducing additional entry that quickly dissipates rents. This "preemption" behavior is beyond the capability of our current framework and warrants future research.

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Figure 1 Illustration: How Our Model Identifies Entry Costs

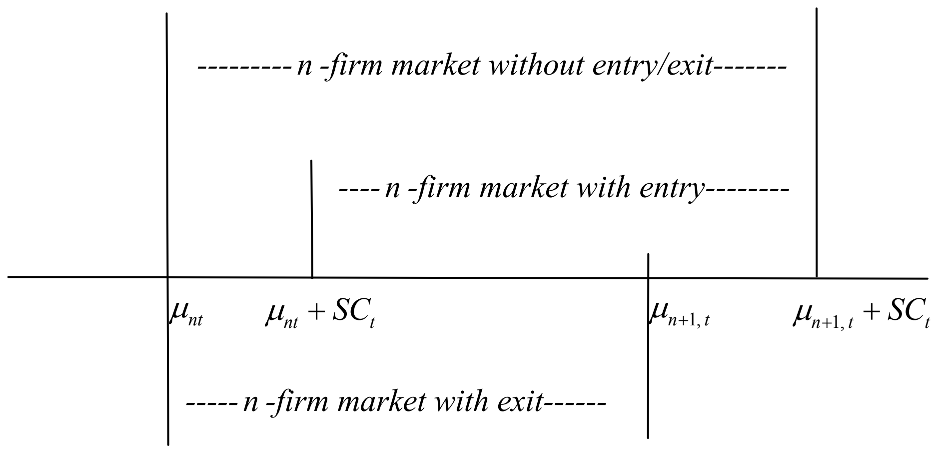
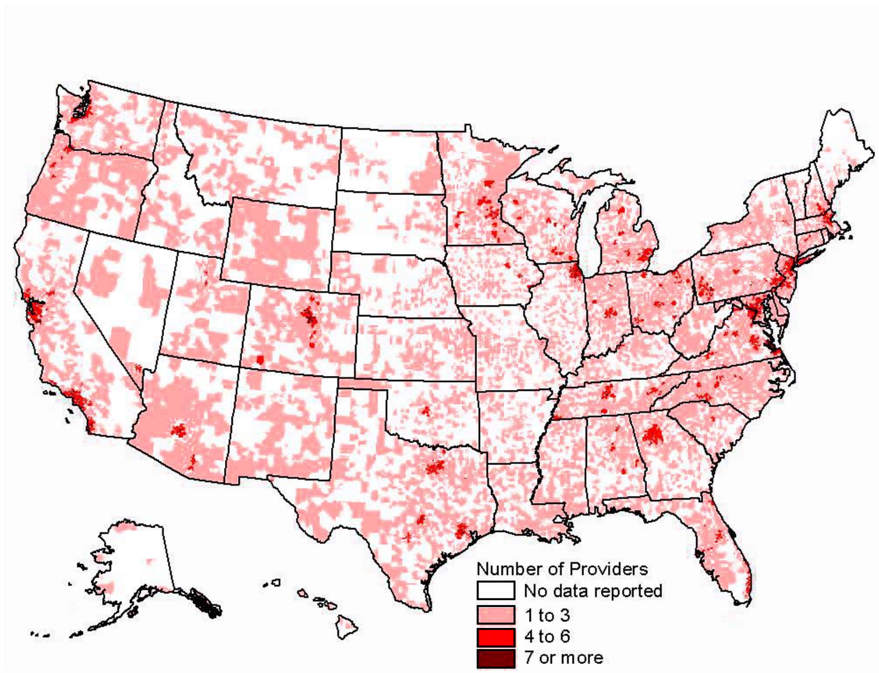


Figure 2 Broadband Distribution by Number of Providers per Zip Code

December 1999



December 2003

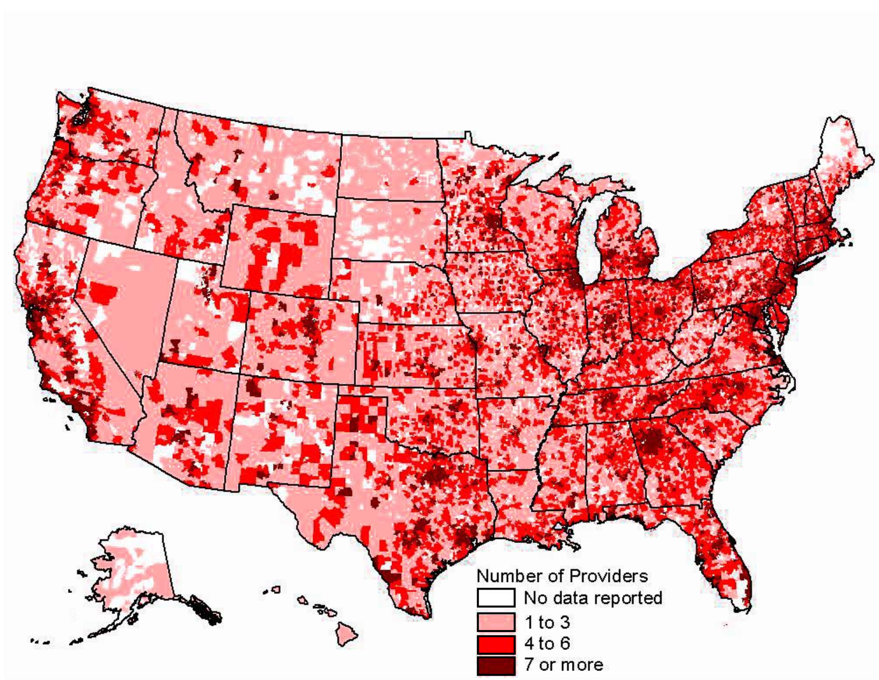


Table 1 Summary Statistics on Firm Entry, Exit, and Incumbency

Variable	Mean	Standard Error	Min	Max
Number of providers in a zip code market				
Dec 1999	0.274	0.519	0	9
Jun 2000	0.364	0.602	0	11
Dec 2000	0.485	0.795	0	15
Jun 2001	0.562	0.850	0	14
Dec 2001	0.597	0.885	0	14
Jun 2002	0.724	1.034	0	16
Dec 2002	0.827	1.106	0	17
Jun 2003	0.976	1.282	0	16
Dec 2003	1.087	1.377	0	17
Zip code market has net entry in the 6 month period (yes=1, no=0)				
Dec 1999—Jun 2000	0.111	0.314	0	1
Jun 2000—Dec 2000	0.114	0.318	0	1
Dec 2000—Jun 2001	0.134	0.341	0	1
Jun 2001—Dec 2001	0.086	0.280	0	1
Dec 2001—Jun 2002	0.115	0.319	0	1
Jun 2002—Dec 2002	0.114	0.318	0	1
Dec 2002—Jun 2003	0.109	0.311	0	1
Jun 2003—Dec 2003	0.090	0.286	0	1
Zip code market has no net entry or exit in the 6 month period (yes =1, no=0)				
Dec 1999—Jun 2000	0.863	0.344	0	1
Jun 2000—Dec 2000	0.864	0.343	0	1
Dec 2000—Jun 2001	0.798	0.402	0	1
Jun 2001—Dec 2001	0.854	0.353	0	1
Dec 2001—Jun 2002	0.860	0.347	0	1
Jun 2002—Dec 2002	0.852	0.355	0	1
Dec 2002—Jun 2003	0.867	0.340	0	1
Jun 2003—Dec 2003	0.886	0.318	0	1

Table 2 Percentage of Zip Codes with n Firms

	Dec99	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
$n=0$	73.95	65.86	57.78	51.78	49.72	42.40	35.67	30.79	26.96
$n=1-3$	25.72	33.59	40.70	46.24	47.87	53.86	59.64	61.83	63.67
$n=4$	0.17	0.31	0.92	1.25	1.55	2.38	3.08	4.85	6.02
$n=5$	0.06	0.08	0.24	0.31	0.40	0.63	0.81	1.44	1.99
$n=6$	0.04	0.06	0.13	0.16	0.17	0.29	0.27	0.40	0.56
$n\geq 7$	0.05	0.10	0.23	0.26	0.30	0.42	0.53	0.70	0.80
$N=14364$	100%	100%	100%	100%	100%	100%	100%	100%	100%

Table 3 Summary Statistics of Zip Code Demographics

Variable	Definition	Mean*	Standard Error	Min	Max
pop/1000	# people living in a zip code, in thousands	1.018	0.742	0.001	2.729
% Black	% population: African Americans	0.050	0.141	0	1
% Hispanic	% population: Hispanics	0.037	0.103	0	1
% Native	% population: Native American	0.022	0.110	0	1
% Asian	% population: Asians	0.004	0.024	0	1
m_income	Household median income	35443	13542	0	200k
% college	% population over 25 with some college education	0.383	0.156	0	1
hh_size	Average household size	2.563	0.340	0	10.25
% female	% population: females	0.498	0.039	0	1
% senior	% population over 60	0.327	0.086	0	1
% w_home	% working population over 16 working at home	0.054	0.058	0	1
% long_cmu	% working population over 16 spending more than 40 minutes on commuting	0.204	0.137	0	1
% rent	% households renting	0.201	0.118	0	1
% phone	% households with a telephone at home	0.956	0.063	0	1
% rural	% population living in rural areas	0.921	0.249	0	1
firm density	# firms per thousand of population in county, 1998	23.985	6.890	3.196	102.67
land area	square miles of land area	53.76	74.02	0.002	918.45
pop density	# people per square mile	188.8	539.2	2.6	5221

*: This column reports the simple-average of variables across zip codes.

Table 4 Patterns on Firm Entry and Incumbency over Time

	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
% of n -firm Markets with Net Entry								
Markets with								
$n=0$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$n=1-3$	**31.73**	**25.01**	**26.18**	**15.15**	**17.18**	**15.07**	**10.60**	**7.49**
$n=4$	77.27	87.88	71.11	58.11	62.28	54.07	58.76	42.13
$n=5$	72.73	91.43	75.00	59.65	70.33	59.83	69.57	57.34
$n=6$	77.78	83.33	52.17	62.50	57.14	48.72	75.86	65.43
$n \geq 7$	66.67	57.58	28.95	27.91	37.70	26.32	25.00	19.13
% of n -firm Markets with No Net Entry/Exit								
Markets with								
$n=0$	96.09	96.35	88.21	89.54	95.40	93.68	94.60	96.44
$n=1-3$	**68.12**	**74.87**	**72.58**	**83.54**	**82.12**	**83.49**	**88.50**	**90.95**
$n=4$	18.18	10.61	23.33	34.23	33.92	38.69	37.50	51.74
$n=5$	18.18	5.71	15.91	24.56	25.27	33.33	26.57	36.71
$n=6$	11.11	11.11	21.74	16.67	30.95	41.03	24.14	30.86
$n \geq 7$	33.33	42.42	71.05	72.09	62.30	73.68	75.00	80.87

Table 5 Ordered Probit Results for BR Replication

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dec99	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
pop/1000	**0.507**	**0.575**	**0.649**	**0.832**	**0.850**	**0.902**	**0.945**	**0.950**	**0.971**
	(0.016)***	(0.016)***	(0.015)***	(0.016)***	(0.016)***	(0.016)***	(0.017)***	(0.017)***	(0.017)***
% Black	-0.169	-0.382	-0.146	-0.009	-0.033	0.091	0.216	0.105	0.134
	(0.098)*	(0.095)***	(0.087)*	(0.087)	(0.085)	(0.083)	(0.082)***	(0.081)	(0.080)*
% Hispanic	-0.495	-0.509	-0.170	0.158	0.085	-0.222	-0.185	-0.355	-0.501
	(0.142)***	(0.134)***	(0.119)	(0.116)	(0.115)	(0.113)*	(0.111)*	(0.110)***	(0.110)***
% Native	-0.540	-0.578	-0.886	-0.733	-0.222	-0.284	-0.191	-0.196	-0.143
	(0.176)***	(0.163)***	(0.161)***	(0.146)***	(0.128)*	(0.123)**	(0.121)	(0.119)*	(0.116)
% Asian	1.225	0.903	1.404	1.576	0.405	1.513	1.737	1.541	1.414
	(0.427)***	(0.416)**	(0.405)***	(0.406)***	(0.411)	(0.405)***	(0.409)***	(0.405)***	(0.406)***
ln(m_incom)	0.305	0.333	0.439	0.575	0.517	0.594	0.549	0.557	0.573
	(0.051)***	(0.048)***	(0.046)***	(0.047)***	(0.046)***	(0.045)***	(0.044)***	(0.043)***	(0.043)***
% college	0.357	0.718	0.563	0.931	0.812	0.544	0.533	0.518	0.333
	(0.103)***	(0.097)***	(0.094)***	(0.095)***	(0.093)***	(0.091)***	(0.090)***	(0.088)***	(0.088)***
hh_size	-0.112	-0.172	-0.219	-0.287	-0.282	-0.308	-0.320	-0.265	-0.236
	(0.052)**	(0.049)***	(0.048)***	(0.047)***	(0.046)***	(0.045)***	(0.044)***	(0.044)***	(0.043)***
% female	-1.648	-1.386	-1.135	-1.421	-1.366	-1.592	-1.452	-1.381	-1.357
	(0.312)***	(0.299)***	(0.286)***	(0.286)***	(0.283)***	(0.278)***	(0.277)***	(0.273)***	(0.272)***
% senior	0.148	-0.008	-0.288	-0.077	-0.159	-0.370	-0.386	-0.192	-0.398
	(0.189)	(0.180)	(0.175)*	(0.175)	(0.173)	(0.170)**	(0.169)**	(0.165)	(0.164)**
% w_home	0.532	0.387	0.092	0.441	0.346	0.474	0.536	0.511	0.573
	(0.234)**	(0.222)*	(0.216)	(0.213)**	(0.211)	(0.206)**	(0.205)***	(0.201)**	(0.200)***

% long_cmu	0.894	0.974	0.847	0.284	0.326	0.234	0.367	0.350	0.177
	(0.094)***	(0.090)***	(0.086)***	(0.089)***	(0.088)***	(0.086)***	(0.084)***	(0.083)***	(0.082)**
% rent	0.606	1.038	0.830	1.239	1.204	1.129	1.094	1.143	1.143
	(0.119)***	(0.114)***	(0.110)***	(0.109)***	(0.108)***	(0.106)***	(0.105)***	(0.103)***	(0.102)***
% phone	0.995	1.042	0.790	0.411	-0.011	0.119	0.481	0.713	0.877
	(0.288)***	(0.271)***	(0.251)***	(0.249)*	(0.230)	(0.223)	(0.221)**	(0.218)***	(0.215)***
% rural	-0.568	-0.385	-0.423	-0.421	-0.454	-0.463	-0.502	-0.573	-0.557
	(0.058)***	(0.056)***	(0.054)***	(0.056)***	(0.055)***	(0.054)***	(0.054)***	(0.053)***	(0.052)***
firm density	0.008	0.012	0.004	-0.002	0.002	-0.000	0.002	0.003	0.004
	(0.002)***	(0.002)***	(0.002)**	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)*	(0.002)**
ln(pop_dsty)	-0.006	0.012	-0.007	-0.095	-0.083	-0.100	-0.142	-0.179	-0.196
	(0.011)	(0.010)	(0.009)	(0.010)***	(0.010)***	(0.009)***	(0.009)***	(0.009)***	(0.009)***
μ_{1-3}	4.310	5.159	5.367	5.873	4.859	5.127	4.737	5.007	4.982
	(0.412)***	(0.327)***	(0.276)***	(0.251)***	(0.255)***	(0.228)***	(0.217)***	(0.195)***	(0.189)***
μ_4	6.713	7.699	7.728	8.419	7.357	7.657	7.380	7.543	7.521
	(0.340)***	(0.268)***	(0.242)***	(0.223)***	(0.232)***	(0.209)***	(0.200)***	(0.183)***	(0.179)***
μ_5	7.004	8.051	8.164	8.911	7.865	8.184	7.948	8.159	8.145
	(0.328)***	(0.235)***	(0.221)***	(0.201)***	(0.213)***	(0.197)***	(0.187)***	(0.174)***	(0.173)***
μ_6	7.187	8.206	8.390	9.148	8.137	8.476	8.271	8.555	8.584
	(0.362)***	(0.279)***	(0.236)***	(0.218)***	(0.219)***	(0.204)***	(0.184)***	(0.169)***	(0.170)***
μ_7	7.378	8.383	8.561	9.342	8.312	8.698	8.442	8.746	8.809
	(0.425)***	(0.341)***	(0.291)***	(0.266)***	(0.267)***	(0.239)***	(0.227)***	(0.205)***	(0.199)***
$\ln L$	-7656.7	-8465.2	-9460.4	-9260.6	-9556.4	-9970.5	-9938.7	-10625.3	-10975.7

Note: Numbers in parenthesis are standard errors for all tables reporting estimation results. * significant at 10% level, ** significant at 5%, and *** significant at 1%.

Table 6a Entry Thresholds: BR Replication Results

Population (in thousands) Necessary to Support n firms									
	Dec99	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
$n=1-3$	2.420	1.828	1.363	1.082	0.999	0.738	0.510	0.330	0.186
$n=4$	7.132	6.228	4.991	4.137	3.930	3.536	3.303	2.995	2.797
$n=5$	7.702	6.839	5.663	4.728	4.527	4.119	3.903	3.643	3.439
$n=6$	8.062	7.108	6.010	5.012	4.846	4.442	4.245	4.059	3.891
$n\geq 7$	8.436	7.414	6.273	5.245	5.051	4.688	4.425	4.259	4.123

Table 6b Entry Threshold Ratios: BR Replication Results

	Dec99	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
$\frac{s_4}{s_1}$	0.737	0.852	0.916	0.956	0.984	1.198	1.618	2.269	3.759
$\frac{s_4}{s_{1-3}}$ *revised*	**1.210**	**1.435**	**1.624**	**1.776**	**1.841**	**2.268**	**3.129**	**4.423**	**7.519**
$\frac{s_5}{s_4}$	0.864	0.878	0.908	0.914	0.921	0.932	0.945	0.973	0.984
$\frac{s_6}{s_5}$	0.872	0.866	0.884	0.884	0.892	0.899	0.906	0.929	0.943
$\frac{s_7}{s_6}$	0.897	0.894	0.895	0.897	0.893	0.905	0.893	0.899	0.908

Note: We calculate entry thresholds (table 6a) and entry threshold ratios (table 6b) using the coefficient estimates in table 5. We also calculate the standard errors for entry thresholds and entry threshold ratios using the Delta method. In table 6a and 6b, all estimates are at least significant at 10% level; the majority of them are significant at 1% level. To save space, we do not report standard errors in these tables. Similarly, we do not report standard errors in table 8a, 8b, 11b, and 11c.

Table 7 MLE Results for the Baseline Model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
pop/1000	**0.411**	**0.463**	**0.659**	**0.514**	**0.574**	**0.593**	**0.595**	**0.597**
	(0.020)***	(0.020)***	(0.018)***	(0.020)***	(0.021)***	(0.021)***	(0.021)***	(0.023)***
% Black	-0.371	0.170	0.136	0.033	0.238	0.354	-0.049	0.166
	(0.119)***	(0.093)*	(0.093)	(0.101)	(0.104)**	(0.093)***	(0.096)	(0.103)
% Hispanic	-0.305	0.216	0.378	0.024	-0.450	-0.017	-0.211	-0.398
	(0.180)*	(0.131)	(0.139)***	(0.148)	(0.127)***	(0.143)	(0.144)	(0.163)**
% Native	-0.388	-0.863	-0.429	0.281	-0.221	0.031	-0.071	0.027
	(0.225)*	(0.230)***	(0.154)***	(0.134)**	(0.152)	(0.163)	(0.167)	(0.153)
% Asian	0.567	1.971	1.421	-0.527	1.932	1.039	0.824	0.398
	(0.428)	(0.321)***	(0.350)***	(0.325)	(0.318)***	(0.428)**	(0.462)*	(0.525)
ln(m_incom)	0.270	0.429	0.480	0.269	0.484	0.316	0.420	0.398
	(0.049)***	(0.047)***	(0.038)***	(0.051)***	(0.043)***	(0.043)***	(0.041)***	(0.046)***
% college	0.792	0.177	0.949	0.363	0.096	0.327	0.356	-0.055
	(0.115)***	(0.113)	(0.099)***	(0.112)***	(0.105)	(0.108)***	(0.103)***	(0.111)
hh_size	-0.243	-0.243	-0.254	-0.231	-0.246	-0.223	-0.118	-0.102
	(0.061)***	(0.051)***	(0.042)***	(0.046)***	(0.049)***	(0.052)***	(0.050)**	(0.062)
% female	-0.825	-0.694	-1.239	-1.124	-1.289	-0.989	-0.880	-0.788
	(0.296)***	(0.272)**	(0.275)***	(0.286)***	(0.259)***	(0.259)***	(0.274)***	(0.338)**
% senior	-0.211	-0.583	0.080	-0.220	-0.454	-0.159	0.161	-0.433
	(0.210)	(0.197)***	(0.182)	(0.196)	(0.196)**	(0.203)	(0.198)	(0.235)*
% w_home	0.149	-0.022	0.569	0.215	0.450	0.432	0.131	0.401
	(0.247)	(0.249)	(0.257)**	(0.245)	(0.232)*	(0.271)	(0.275)	(0.315)
% long_cmu	0.693	0.427	-0.164	0.296	0.066	0.408	0.226	-0.178
	(0.121)***	(0.115)***	(0.102)	(0.110)***	(0.110)	(0.104)***	(0.109)**	(0.118)

% rent	1.224	0.488	1.158	0.836	0.697	0.846	0.874	0.746
	(0.130)***	(0.116)***	(0.105)***	(0.120)***	(0.111)***	(0.110)***	(0.109)***	(0.120)***
% phone	0.589	0.216	-0.135	-0.354	0.128	0.707	0.642	0.683
	(0.315)*	(0.309)	(0.270)	(0.250)	(0.270)	(0.300)**	(0.274)**	(0.331)**
% rural	-0.107	-0.440	-0.374	-0.372	-0.424	-0.437	-0.507	-0.372
	(0.075)	(0.070)***	(0.066)***	(0.071)***	(0.067)***	(0.066)***	(0.066)***	(0.070)***
firm density	0.011	-0.006	-0.006	0.005	-0.001	0.005	0.004	0.004
	(0.002)***	(0.002)***	(0.002)***	(0.002)**	(0.002)	(0.002)**	(0.002)*	(0.002)*
ln(pop_dsty)	0.022	-0.022	-0.129	-0.032	-0.065	-0.117	-0.127	-0.109
	(0.013)	(0.013)	(0.012)***	(0.013)**	(0.013)***	(0.013)***	(0.013)***	(0.014)***
μ_{1-3}	2.467	2.186	3.014	0.714	2.214	1.474	2.533	1.977
	(0.493)***	(0.499)***	(0.375)***	(0.502)***	(0.426)***	(0.408)***	(0.398)***	(0.446)***
μ_4	4.366	3.713	4.878	2.216	3.762	3.131	3.886	3.320
	(0.448)***	(0.477)***	(0.356)***	(0.496)***	(0.415)***	(0.400)***	(0.392)***	(0.440)***
μ_5	4.731	4.152	5.353	2.688	4.243	3.647	4.424	3.815
	(0.422)***	(0.462)***	(0.342)***	(0.490)***	(0.407)***	(0.393)***	(0.388)***	(0.440)***
μ_6	4.893	4.407	5.618	2.987	4.560	3.988	4.843	4.254
	(0.468)***	(0.476)***	(0.359)***	(0.499)***	(0.414)***	(0.391)***	(0.386)***	(0.441)***
μ_7	5.099	4.608	5.840	3.213	4.816	4.169	5.097	4.551
	(0.519)***	(0.522)***	(0.402)***	(0.528)***	(0.445)***	(0.430)***	(0.417)***	(0.465)***
SC_t	2.208	2.387	1.684	2.044	2.382	2.247	2.486	2.702
	(0.032)***	(0.033)***	(0.027)***	(0.028)***	(0.033)***	(0.030)***	(0.033)***	(0.035)***
$\ln L$	-5544.2	-5869.3	-6992.2	-6289.6	-6050.6	-6208.6	-6340.5	-5783.3

Table 8a Entry Thresholds: the Baseline Model

Population (in thousands) Needed to Support n firms								
	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
$n = 1-3$	3.606	3.101	2.124	2.829	2.239	1.942	1.979	2.024
$n = 4$	8.220	6.403	4.954	5.748	4.934	4.734	4.252	4.271
$n = 5$	9.107	7.352	5.676	6.666	5.772	5.604	5.157	5.100
$n = 6$	9.501	7.904	6.078	7.247	6.324	6.178	5.861	5.836
$n \geq 7$	10.001	8.336	6.415	7.687	6.769	6.483	6.288	6.333

Note: We calculate entry thresholds (Table 8a) and entry threshold ratios (Table 8b) using the coefficient estimates in table 7. We also calculate the standard errors for entry thresholds and entry threshold ratios using the Delta method. In table 8a and 8b, all estimates are at least significant at 10% level; the majority of them are significant at 1% level.

Figure 3 Entry Thresholds over Time

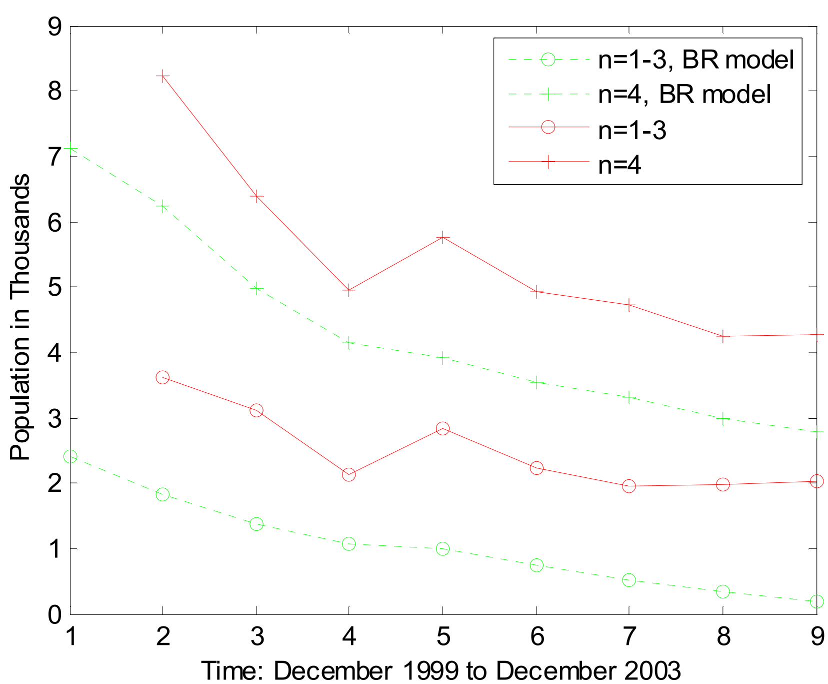


Table 8b Entry Threshold Ratios: the Baseline Model

	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
$\frac{s_4}{s_1}$	0.570	0.516	0.583	0.508	0.551	0.610	0.537	0.528
$\frac{s_4}{s_{1-3}}$ *revised*	**0.960**	**0.915**	**1.084**	**0.951**	**1.043**	**1.179**	**1.047**	**1.055**
$\frac{s_5}{s_4}$	0.886	0.919	0.917	0.928	0.936	0.947	0.970	0.955
$\frac{s_6}{s_5}$	0.869	0.896	0.892	0.906	0.913	0.919	0.947	0.954
$\frac{s_7}{s_6}$	0.902	0.904	0.905	0.909	0.917	0.899	0.920	0.930

Figure 4 Entry Threshold Ratios over Time

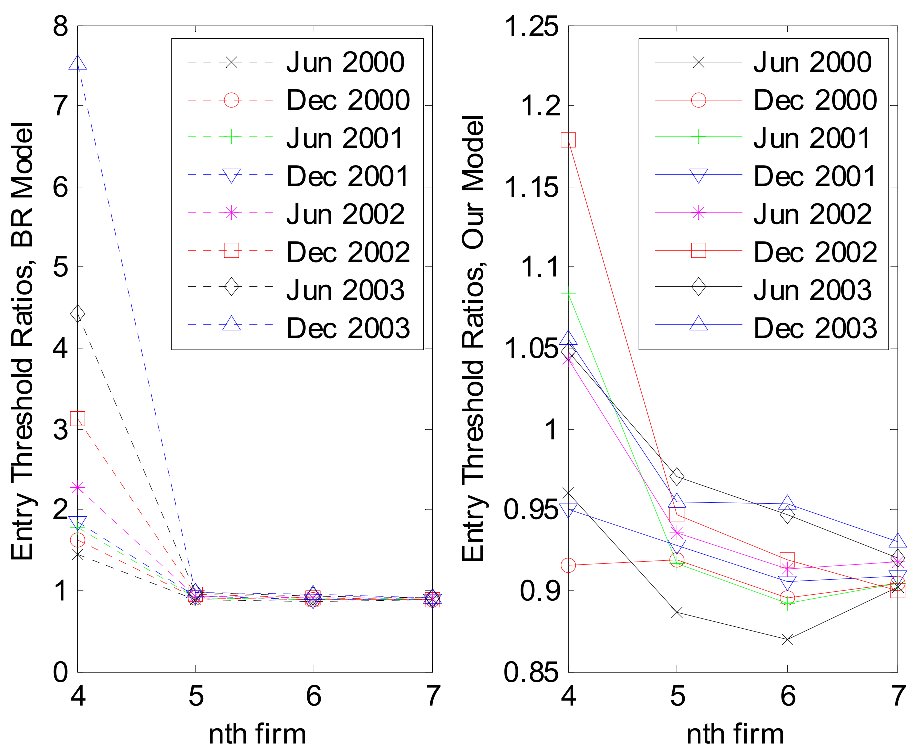


Table 9 Likelihood Ratio Tests for Constant Entry Threshold Ratios over Time

	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
Test for $\frac{s_{4t}}{s_{1-3,t}} = \frac{s_{4,t-1}}{s_{1-3,t-1}}$	0.022	14.960***	9.139***	4.599**	2.037	0.461	0.910
Test for $\frac{s_{4t}}{s_{1-3,t}\ revised} = \frac{s_{4,t-1}}{s_{1-3,t-1}\ revised}$	4.834**	89.032***	28.710***	31.992***	44.590***	24.662***	0.096
Test for $\frac{s_{5t}}{s_{4t}} = \frac{s_{5,t-1}}{s_{4,t-1}}$	5.505**	3.539*	0.148	2.909*	1.349	12.470***	0.747
Test for $\frac{s_{6t}}{s_{5t}} = \frac{s_{6,t-1}}{s_{5,t-1}}$	4.288**	3.779*	0.132	2.653	0.502	13.538***	1.835
Test for $\frac{s_{7t}}{s_{6t}} = \frac{s_{7,t-1}}{s_{6,t-1}}$	0.777	4.165**	0.541	2.687	0.852	9.631***	2.635

Table 10a MLE Results: Extension 1, $SC_{1-3,t} \neq SC_{4t} = SC_{5t} = SC_{6t} = SC_{7t}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
$SC_{1-3,t}$	2.199	2.377	1.661	2.038	2.372	2.248	2.492	2.872
	(0.033)***	(0.034)***	(0.028)***	(0.029)***	(0.034)***	(0.033)***	(0.036)***	(0.042)***
$SC_{4t} = SC_{5t}$ $= SC_{6t} = SC_{7t}$	2.722	2.732	1.995	2.101	2.449	2.243	2.465	2.429
	(0.210)***	(0.187)***	(0.094)***	(0.082)***	(0.086)***	(0.066)***	(0.063)***	(0.054)***
$\ln L$	-5541.8	-5867.7	-6986.4	-6289.3	-6050.3	-6208.6	-6340.4	-5760.1

Table 10b MLE Results: Extension 1, $SC_{1-3,t} \neq SC_{4t} \neq SC_{5t} = SC_{6t} = SC_{7t}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
$SC_{1-3,t}$	2.199	2.377	1.660	2.037	2.371	2.247	2.490	2.872
	(0.033)***	(0.034)***	(0.028)***	(0.029)***	(0.034)***	(0.033)***	(0.036)***	(0.042)***
SC_{4t}	2.702	2.651	1.921	2.072	2.400	2.208	2.409	2.422
	(0.212)***	(0.203)***	(0.096)***	(0.083)***	(0.089)***	(0.067)***	(0.067)***	(0.055)***
$SC_{5t} = SC_{6t}$ $= SC_{7t}$	2.761	2.834	2.210	2.196	2.559	2.334	2.587	2.445
	(0.276)***	(0.229)***	(0.124)***	(0.112)***	(0.114)***	(0.092)***	(0.084)***	(0.071)***
$\ln L$	-5541.8	-5867.3	-6982.0	-6288.5	-6048.9	-6207.2	-6337.7	-5760.0

Table 10c Likelihood Ratio Tests for Entry Costs Proportionality

	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
Test for $SC_{1-3,t} = SC_{4t} = SC_{5t} = SC_{6t} = SC_{7t}$	4.667**	3.054*	11.665***	0.564	0.755	0.005	0.005	46.448***
Test for $SC_{1-3,t} \neq SC_{4t} = SC_{5t} = SC_{6t} = SC_{7t}$	0.075	0.847	8.791***	1.721	2.685	2.812*	2.812**	0.143

Table 11a MLE Results: Extension 2, Allowing County-level Random Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
σ^2_{county}	0.867	0.697	0.560	0.652	0.462	0.443	0.450	0.489
	(0.016)**	(0.016)***	(0.015)***	(0.016)***	(0.017)***	(0.016)***	(0.016)***	(0.017)***
$\ln L$	-4976.9	-5585.6	-6762.5	-6022.6	-5941.2	-6094.2	-6237.7	-5686.0

Table 11b Entry Thresholds: Extension 2, Allowing County-level Random Effects

Population (in thousands) Needed to Support n firms								
	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
$n = 1-3$	3.720	3.071	2.170	2.898	2.223	1.926	1.946	1.969
$n = 4$	8.249	6.514	5.123	5.928	4.957	4.743	4.241	4.220
$n = 5$	9.034	7.462	5.868	6.846	5.815	5.611	5.152	5.044
$n = 6$	9.388	8.000	6.307	7.431	6.386	6.188	5.879	5.775
$n \geq 7$	9.839	8.422	6.671	7.877	6.848	6.496	6.314	6.281

Table 11c Entry Threshold Ratios: Extension 2, Allowing County-level Random Effects

	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
$\frac{s_4}{s_1}$	0.554	0.530	0.590	0.511	0.557	0.616	0.545	0.536
$\frac{s_4}{s_{1-3}}$ *revised*	**0.934**	**0.940**	**1.097**	**0.957**	**1.055**	**1.191**	**1.062**	**1.072**
$\frac{s_5}{s_4}$	0.876	0.916	0.916	0.924	0.939	0.946	0.972	0.956
$\frac{s_6}{s_5}$	0.866	0.893	0.896	0.905	0.915	0.919	0.951	0.954
$\frac{s_7}{s_6}$	0.898	0.902	0.907	0.908	0.919	0.900	0.921	0.932

Note: In table 11b and 11c, all estimates are at least significant at 10% level; the majority of them are significant at 1% level.