Does the Fourth Entrant Make Any Difference?

Entry and Competition in the Early U.S. Broadband Market*

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Abstract

We study the importance of sunk costs in determining entry conditions and inferences about firm conduct in an adapted Bresnahan and Reiss (1991, 1994) framework. In our framework, entrants incur sunk costs to enter, while incumbents disregard these costs in deciding on continuation or exit. We apply this framework to study entry and competition in the local U.S. broadband markets from 1999 to 2003. Ignoring sunk costs generates unreasonable variation in firms' competitive conduct over time. This variation disappears when entry costs are allowed. Once the market has one to three incumbent firms, the fourth entrant has little effect on competitive conduct.

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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 ensure effective competition. Lack of data on prices, quantities, product characteristics, and cost structures makes it difficult to separate out the demand, technological, and strategic factors determining firms' entry, exit, and market concentration.

A solution proposed in a series of prominent papers by Bresnahan and Reiss (1987, 1990, and 1991) is to link entry thresholds with changes in firms' competitive conduct using cross sectional variation in the number of firms. 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. As prices fall, a larger number of units or customers served are 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 further entry will not generate further changes in firms' competitive conduct. Bresnahan and Reiss (1991) find that once the market has three to five firms, the next entrant makes little difference in the market's competitive conduct.

The Bresnahan and Reiss (henceforth BR) methodology has become enormously influential in the field of empirical industrial organization. The combination of a reduced-form profit function with a game theoretic model of entry and competition allows inferences to be drawn about firms' strategic behavior from available data on market structure. However, BR have always been clear about the limitations to their methodology. First, the procedure is best suited to geographically distinct local service markets so that researchers can clearly define market boundaries. 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 entry threshold ratios vary significantly across industries, implying large differences in competitive conduct across industries.[1] These large differences in threshold ratios may suggest more variation in competitive conduct than actually exists. Differences in sunk costs or regulatory environment across industries are suggested, but not really investigated. Lastly, BR's framework is based on cross sectional observations of markets in long-run equilibrium. A more realistic entry game needs to capture the dynamic feature of entry and exit, especially in markets where long-run equilibrium has not been achieved.

In a 1994 article, BR more directly explore the importance of sunk costs on entry and exit dynamics using two repeated cross-sections of data on the location of rural dentists. 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, their paper does illustrate that sunk costs can have large effects on estimated thresholds, and therefore, researchers' inference about firm conduct, even in a relatively stagnant service industry.

After BR's seminal work, the literature on empirical entry games has progressed along two lines. The first extends the static BR framework to accommodate differences among firms into the model instead of imposing the BR assumption of homogeneous firms.[2] Many of these papers consider growing industries rather than the relatively stable rural retail and professional sectors used in the BR analysis, but these papers rarely discuss the role of sunk costs on entry. The other line initiated by Ericson and Pakes

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

[2] Berry (1992) allows firm-specific error terms in his study of the airline market. Toivanen and Waterson (2000, 2004) and Jia (2007) distinguish leaders and followers in the analysis of the UK fast food market and U.S discount retail industries. Mazzeo (2002 a, b), Dranove, Gron, and Mazzeo (2003), Greenstein and Mazzeo (2006), and Cohen and Mazzeo (2007) introduce quality differentiation into the BR framework in studies of motel, HMO, telecommunication markets, and retail depository institutions. Danis (2003) makes use of the identities of local exchanges in analyzing the equity option market. Seim (2005) allows firms to possess private information in the video retail industry.

(1995) studies dynamic oligopoly entry games. In a dynamic setting, a potential entrant compares the discounted expected future payoff of entry to the sunk costs of entry. These entry costs play a pivotal role in determining market structure and industry evolution. The distribution of entry cost is usually recovered from the distribution of entry decisions, conditioning on some market-level attributes determining post-entry payoffs (Aguirregabiria & Mira, 2007; Bajari, Benkard & Levinson, 2007; Pakes, Ostrovsky & Berry, 2007; Pesendorfer & Schmidt-Dengler, 2003). These models, which are more general and realistic compared to the static entry models, are however much more complicated to estimate and require data on the identities of entrants and their timing of entry (Collard-Wexler, 2008; Ryan, 2009; Dunne, Klimek, Roberts, & Xu, 2009).

We draw from both lines of these literatures, incorporating the sunk entry costs central to the dynamic entry games into BR's 1991 framework and 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. 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.

Our strategy keeps the basic econometric framework of BR 1991 intact and uses BR 1994's idea about entry and exit thresholds. Our method differs from BR 1994 in our adaptation of the original static BR framework, which is more transparent in identification and more tractable in computation.[3] In terms of modeling, ours concedes to the richer, more general dynamic models of entry as referenced above.

[3] We also follow the convention in later research by using a reduced form profit function that does not distinguish between variable profits and fixed costs of production.

With more readily available cross-sectional data on market structure, however, our model may offer an improvement over the original BR framework because researchers often lack data to bring a full blown dynamic model of entry to estimation.

We apply our adapted framework to time series observations of zip-code-level local market structure for providers of high-speed lines for Internet access in the United States. The commercial provision of broadband services has expanded rapidly since 1998. The Federal Trade 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. 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. Like other telecommunication industries, the competitive conduct of this thriving market has been subject to scrutiny.[4] An important policy goal of the FCC is to promote competition in the marketplace by encouraging the entry of smaller, competitive providers. To achieve this policy goal, several questions must be addressed: What factors encourage or deter provider entry in a local market? How many providers must exist in a local market to reduce or eliminate market power? Do entry costs vary with the order of entry? Is the industry becoming increasing competitive over time? Our empirical model can address all of these questions, showing the relationship between the number of providers in a local broadband market and competitive conduct, and how that relationship has changed over time.

Our empirical findings are striking. Results without sunk entry costs imply that entry conditions vary dramatically over time for the 4^{th} firm entering a 1-to-3 firm local oligopoly market. In particular, entry conditions become increasingly more difficult for the 4^{th} firm. This unreasonable variation in entry conditions disappears when the estimation accommodates entry and exit. Entry conditions for the 4^{th} firm and subsequent entrants are stable, implying that new firm entrants beyond the first three firms have little

[4] For policy debate and strategic conduct in the telecommunication industries, see the work of Augereau, Greenstein, and Rysman (2005), Greenstein (2000), and Greenstein and Mazzeo (2006) and the edited volume by Crandall and Alleman (2002).

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. Although our results are subject to empirical misspecification due to data limitation ---- in particular, the FCC lumps 1 to 3 local providers into a single category ---- we believe our work conveys a clear message that calls for the use of more dynamic entry models to generate accurate assessments of industry competitive environment.

The paper proceeds as follows. Section 2 describes our methodology. Section 3 introduces the broadband market and the data we use. Section 4 presents empirical results. Section 5 concludes.

2. METHODOLOGY

2.1 Sunk Costs and the Dynamic BR Framework

BR (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.[5] 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 2nd firm is four times that necessary to induce entry of the 1st firm, then firms' variable profits and competitive conduct must have changed drastically in moving from a monopoly to a duopoly regime. Therefore, the

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

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.[6]

The static BR framework can be easily estimated using commonly available cross-sectional data on market structure, however, it abstracts away timing of entry and exit, firm and product heterogeneity, incumbents' and entrants' expectations about post-entry competition, and most importantly, "the size and sunkness of set-up costs"(Berry & Reiss, 2006). Theory has been abundant on the central role of sunk costs on firms' strategic entry decisions. In the most straightforward way, sunk costs are irreversible, unrecoverable, direct investment costs for entrants to start businesses.[7] However, there are at least three 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.[8] 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. Lastly, when potential entrants decide to enter under less-than-perfectly predictable market conditions, they give up the option to wait for new information about the likely return of their investment (Pindyck, 2005). Forgone benefits can be interpreted as costs, and since entry is an irreversible decision, these costs are sunk.

[6] See Bresnahan and Reiss (1991) section II for how entry threshold ratios change with minimum efficient scale in a Cournot oligopoly model.
[7] Expenses avoidable if the firm decides to exit, such as rental fees, should not be considered sunk costs.
[8] 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 (1992).

To distinguish between these different types of sunk costs calls for a full-fledged dynamic model (such as Ericson and Pakes, 1995) and detailed firm-level data over several time periods.[9] Even equipped with the right theory and data, estimation is often plagued with complicated econometric and computation issues. A practical solution and a first step into the topic is to focus on the difference in expected future returns between entrants and incumbents. The goal is to quantify the size of overall sunk costs. BR (1994) propose that the differences between entry and exit thresholds provide information about the magnitude of sunk costs. They 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 observations on rural dentists. 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. With all these limitations, however, BR demonstrate convincingly the existence of significant sunk costs and their impact on inferences regarding competition conduct. Their original static framework implied that the entry of the 2nd firm significantly changed the competitive conduct in the local market while the third entrant had little effect. Allowing for sunk entry costs, the 2-stage dynamic framework indicated that even the 2nd entrant does not change competition. This result, in some sense, is even more intriguing than their previous static result, as it implies that the mere existence of potential entrants might be sufficient to warrant effective competition.

Along this line, we develop an adaptation of the BR (1994) model for an industry characterized by significant entry and exit, allowing for differences in sunk costs between entrants and incumbents. We then apply a variant of the original static BR framework to the same industry for a comparison with our adapted model. We show that exploiting the temporal entry and exit patterns of this industry allows us to derive conclusions regarding market structure and competitive conduct that seem more plausible than

[9] Aguirregabiria and Mira (2007), Bajari, Benkard & Levinson (2007), Pakes, Ostrovsky & Berry (2007), and Pesendorfer & Schmidt-Dengler (2003) provide simplifications along this line in order to alleviate the computational burden of estimating a discrete dynamic game, but the data requirement is similar.

those based on the original static framework. Our adaptation does not have the econometric and computational complications of a full-fledged dynamic model. The estimation stays simple, the data requirement remains low, and the identification of sunk costs is transparent. We do want to caution that our framework does not supplant estimation of the real dynamic model when feasible. After all, entry and exit are strategic, dynamic choices which can only be fully understood in a dynamic model with strategic interactions.

2.2 Our Baseline Model

This model focuses on a key difference between new entrants and incumbents observed in any snap shot of a growing market. A potential entrant enters a market when its expected discounted value of future profits exceeds sunk entry costs, while an incumbent firm continues operation when its expected discounted value of future profits exceeds zero. Therefore the existence of sunk entry costs means that it takes less demand to sustain an incumbent than to support a new entrant. 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 sunk entry costs and their roles in determining entry thresholds.

At time period t, there are $N_{mt} = n \quad (n = 0,1,2,...)$ firms operating in market m, where N_{mt} is the observed number of firms in market m at time t. 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 their ex-ante expected market demand, technological change, and competition with other firms. In equilibrium, firms' expectations are realized. The n^{th} firm considering entry into (or continuing operation in) market m which has $n-1$ incumbent firms at time t has an expected discounted value of future profits of:

$$(1) \qquad \Pi_{mt}^{n} = Pop_m * \beta_t^{pop} + X_m * \beta_t - \mu_t^n I\left(N_{mt} = n\right) + \varepsilon_{mt} .$$

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.[10] 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. $I\left(N_{mt}=n\right)$ is an indicator function which transforms the market structure of the market into data and μ_t^n is the (expected and realized) effect on per-firm variable profits of the n^{th} firm entering the market at time t. ε_{mt} denotes 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 variance of the error term is later normalized to one because it cannot be identified in a discrete choice entry framework. The *i.i.d.* assumption about ε_{mt} will be relaxed in an extension to this baseline model.

Note the above setup assumes away simultaneous entry and exit, and instead focuses on the marginal entering or existing firm's expected profitability from operating in the next period. For example, net entry of one firm into an n-firm market may be the result of four new entrants and three exiting firms. Instead of modeling all individual firms' entry and exit decision, we model the marginal entrant's

[10] Section 3 will offer a detailed discussion on the components of X_m. Note that there may be market attributes observed by firms that are not available to the econometrician and therefore we offer an extension of the model in section 2.4 to account for market-level heterogeneity.

expected long-run profits of being the $n+1^{th}$ firm operating in the next period. In other words, we do not include firm-level idiosyncratic shocks which are necessary to evaluate separately the decisions of some firms to enter at the same time that other firms are opting to exit. We make this simplification because our data does not identify firm identities or their timing of entry. As all we observe is net entry or exit, there is no empirical gain from modeling entry at the individual firm level.

Also note that in the formulation of equation (1) we adopt a reduced form profit function in contrast to the more structured profit function in the BR framework. BR define profits by market size times variable profits then subtract fixed operating costs, with each of these three elements defined as a reduced-form linear function. The advantage of such structure is that researchers can allow the number of competing firms to enter the variable profits function and the fixed costs function separately, and thus allow for different interpretation about the role of market structure. Later researchers do not make this distinction, modeling profit by a single reduced form equation (see Berry (1992), Mazzeo (2002 a, b), and Seim (2005) for notable examples). This is because they usually do not have separate measures of variable profits and fixed costs, and because variable profits do not necessarily increase in proportion to market size.[11] And for the same reasons, we decide to adopt a reduced form profit function.

Now we introduce SC_t as a measure of the time-varying entry costs. The recoverable part of entry costs is part of the sell-off value an incumbent incorporates into the decision of whether or not to exit. Here we normalize the expected future sell-off values to zero.[12] 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.

In the data, there are three possible situations that would generate the observation of n firms in market m at time t:

[11] A larger market size, for instance, usually supports greater product variety and thus generates more variable profits due to product differentiation.

[12] Even if we incorporate a positive selloff value into the model this selloff value cannot be separately identified from the sunk cost and competitive conduct parameters. This normalization will not affect entry threshold ratios or exit threshold ratios.

1) One or more firms have entered and there were fewer than n firms at time $t-1$, or $N_{mt} > N_{m,t-1}$.

For the n^{th} firm, the expected discounted value of entry exceeds sunk costs of entry, while for the $n+1^{st}$ firm not. This can be expressed as:

$$\Pi_{mt}^{n} \geq SC_t \quad \& \quad \Pi_{mt}^{n+1} < SC_t .$$

2) No firm has entered or exited a market with n firms, or $N_{mt} = N_{m,t-1}$.

The n^{th} firm from period $t-1$ has decided to stay because its expected discounted values of continuation exceed 0, while the $n+1^{st}$ firm has expected a loss from entry. That is:

$$\Pi_{mt}^{n} \geq 0 \quad \& \quad \Pi_{mt}^{n+1} < SC_t .$$

3) One or more firms have exited and there were more than n firms at time $t-1$, or $N_{mt} < N_{m,t-1}$.

The market has become unprofitable when more than n firms stayed operating. The marginal firm, the $n+1^{st}$ one, expected that it would be unprofitable to stay in the market; when this firm left, the n^{th} firm expected otherwise. That is:

$$\Pi_{mt}^{n} \geq 0 \quad \& \quad \Pi_{mt}^{n+1} < 0 .$$

The following econometric model can nest the above three situations. For a given market m at time t with n firms providing services, we can write down the likelihood of this individual market structure as:

$$\begin{aligned}
& prob(N_{mt} = n) \\
(2) \quad & = \Phi(Pop_m * \beta_t^{pop} + X_m * \beta_t - \mu_t^n I\left(N_{mt} = n\right) - SC_t * I[N_{mt} > N_{m,t-1}]) \\
& - \Phi(Pop_m * \beta_t^{pop} + X_m * \beta_t - \mu_t^{n+1} I\left(N_{mt} = n+1\right) - SC_t * I[N_{mt} > N_{m,t-1}] - SC_t * I[N_{mt} = N_{m,t-1}])
\end{aligned}$$

where $I[.]$ is an indicator function and $\Phi[.]$ is the cumulative density function of a standard normal distribution. When $I[N_{mt} > N_{m,t-1}] = 1$, we have the first situation; when $I[N_{mt} = N_{m,t-1}] = 1$, we have the second situation; when $I[N_{mt} > N_{m,t-1}] = 0$ and $I[N_{mt} = N_{m,t-1}] = 0$, we have the third situation.[13]

In the above model, we have a unique equilibrium because entrants and incumbents are assumed to be post-entry identical. The identities of entrants and incumbents may be undetermined but their number is unique given market characteristics and model parameters. This follows from the BR solution to the multiple equilibria problem in a typical entry game. The parameter vector to be estimated is $\theta = [\beta_t^{pop}, \beta_t, \mu_t^n, SC_t]$.[14] We then employ maximum likelihood methods to estimate this parameter vector:

$$(3) \qquad \hat{\theta} = \arg\max \sum_{m=1,\dots,M} \ln(prob(N_{mt} = n) \mid \theta).$$

2.3 Interpretation and Identification

In the above model, a critical issue is how we distinguish from SC_t from μ_t^n. In the original BR framework, all firms are incumbents in a long-run equilibrium market structure and the likelihood of observing n firms in market m at time t is:

$$(4) \qquad \begin{aligned} &prob(N_{mt} = n) \\ &= \Phi(Pop_m * \beta_t^{pop} + X_m * \beta_t - \mu_t^n I(N_{mt} = n)) \\ &-\Phi(Pop_m * \beta_t^{pop} + X_m * \beta_t - \mu_t^{n+1} I(N_{mt} = n+1)) \end{aligned}$$

[13] Note in the above formulation, we treat the change from last period's market structure as exogenous. An implicit assumption for the exogeneity to hold is that the change in market structure is driven by a local idiosyncratic shock that was not forecastable when firms in the previous period were forecasting their profits and making their entry, stay, and exit decisions. The implication is that these shocks are independent of last period's error term in the profit function.

[14] 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_t^n.

We can identify the competitive conduct parameter μ_t^n's as the cutoffs in the above ordered Probit model. However, sunk costs of entry play no role in such a framework and thus cannot be identified empirically.

In contrast, our model allows identification of the entry costs even when there are no explicit measures of sunk entry costs. The identification comes from the variation in entry and exit patterns across markets and across time. We employ Figure 1 to illustrate the central idea behind the identification. In Figure 1, the horizontal axis measures a firm's expected profitability without considering the negative impact of competitors. As shown here, the distances from μ_t^n to $\mu_t^n + SC_t$, from $\mu_t^n + SC_t$ to μ_t^{n+1}, and from μ_t^{n+1} to $\mu_t^{n+1} + SC_t$, 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. The extra demand (expressed in population) necessary to sustain a n-firm market with net entry that that to sustain a n-firm market without net entry or exit identifies SC_t.

To spell things out more accurately, we define $S\_entry_t^n$ to be the necessary population to support the total of n firms with net entry from last period in a local market at time t, and $S\_exit_t^n$ the necessary population to support such a market structure without net entry. With the estimates $\hat{\theta}$ and the entrants' expected payoff function, we can calculate $S\_entry_t^n$ by

$$(5) \qquad S\_entry_t^n = \frac{\widehat{\mu_t^n} + \widehat{SC_t} - \overline{X_m} * \widehat{\beta_t}}{\widehat{\beta_t^{pop}}},$$

where $\overline{X_m}$ is the cross-market average of X_m. We can also calculate the exit threshold by

$$(6) \qquad S\_exit_t^n = \frac{\widehat{\mu_t^n} - \overline{X_m} * \widehat{\beta_t}}{\widehat{\beta_t^{pop}}}.$$

As clearly shown from the calculation of the entry and exit thresholds, sunk costs $\widehat{SC_t}$ constitute the difference between the two.

Lastly, define s_t^n to be the necessary population to support the entry of the n^{th} firm. The entry threshold for the n^{th} firm is $s_t^n = S\_entry_t^n / n$, and the entry threshold ratio progressing from n to $n+1$ firms is

$$(7) \qquad \frac{s_t^{n+1}}{s_t^n} = \frac{S\_entry_t^{n+1}/(n+1)}{S\_entry_t^n / n}.$$

2.4 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. Early entrants may have early mover advantages and therefore have lower sunk costs than later entrants. At the same time, later entrants may have accumulated better information and lost less of the option value of waiting. We will not be able to offer conclusive evidence about the underlying reasons for differences in sunk costs, but at least we can offer some evidence on whether there are differences across early and later entrants. The expected discounted value of future payoffs for the n^{th} firm entering market m at time t will be the same as (1), but entry costs vary with the order of entry, as embodied by superscript n in SC_t^n. Accordingly, the likelihood function becomes:

$$\begin{aligned}
& prob(N_{mt} = n) \\
(8) \quad & = \Phi(Pop_m * \beta_t^{pop} + X_m * \beta_t - \mu_t^n I\left(N_{mt} = n\right) - SC_t^n * I[N_{mt} > N_{m,t-1}]) \\
& -\Phi(Pop_m * \beta_t^{pop} + X_m * \beta_t - \mu_t^{n+1} I\left(N_{mt} = n+1\right) - SC_t^n * I[N_{mt} > N_{m,t-1}] - SC_t^n * I[N_{mt} = N_{m,t-1}])
\end{aligned}$$

2.5 *Extension 2: Incorporate Spatially Correlated Market-Level Heterogeneity*

In our baseline model, we assume that variation in market structures is driven by *iid* market-level idiosyncrasies. This is a very restrictive assumption as there is often spatially-correlated unmeasured market-level heterogeneity, which causes firms' entry and exit decisions to be spatially correlated. To solve this problem, we propose a random effects model with an aggregate-market-specific error term in the profit functions. Specifically, firms offering services in the same county may be subject to a county-time-specific shock. We can identify this effect because there are multiple markets within a county. The resulting modification of our baseline model is:

$$\Pi_{mt}^{n} = Pop_m * \beta_t^{pop} + X_m * \beta_t - \mu_t^n I\left(N_{mt} = n\right) + \eta_{county,t} + \varepsilon_{mt} . \tag{9}$$

$\eta_{county,t}$ is a time-varying mean zero error with the following structure:

$$\begin{aligned} & \operatorname{cov}[\eta_{county\_i,t}, \eta_{county\_j,t} \mid X_m] \\ & = \operatorname{var}[\eta_{county,t} \mid X_m] = \sigma_{county,t}^2 \quad \textit{if} \quad county\_i = county\_j; \\ & = 0 \qquad\qquad\qquad\qquad\qquad \textit{otherwise.} \end{aligned} \tag{10}$$

Estimation of this model involves greater computational burden than the baseline model because the likelihood function involves integration over the market random effects $\eta_{county,t}$. The gain from this model is that we can obtain more efficient estimators and understand the role of unobserved market-level heterogeneity on market structures. We use the method of simulated maximum likelihood to estimate this model. Assuming that there are M_c market in county c and there are C counties in total, the simulated likelihood function is given as:

$$\ln L_{simulated} = \sum_{county=1,\ldots,C} \ln\left\{\frac{1}{R}\sum_{r=1}^{R}\left[\prod_{m=1}^{M_c}\left(prob\left(N_{mt}^r = n\right)\right)\right]\right\}. \tag{11}$$

In the above formulation, R denotes the number of simulation draws we use for the county-level random term $\eta_{county,t}$ ---- we set R equal to 50 ---- and N_{mt}^r denotes the simulated market structure under an individual simulation draw r.

3. THE U.S. BROADBAND MARKET AND THE DATA

3.1 The U.S. 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.[15] The vast majority of these lines served residential and small business subscribers.[16] 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)[17] and cable modems using hybrid fiber-coaxial cable networks, operated primarily by cable television operators.[18] 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

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[15] FCC (2004) reports most of the statistics we refer to in this section.
[16] 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.
[17] Asymmetric DSL provide speeds in one direction greater than speeds in the other direction.
[18] 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.

sharp decline in the cost of cable and DSL service. Monthly prices were $27 in many areas in 2004, down 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 market definition hinges on the mobility of consumers' demand and conventionally researchers use criteria focused on demand-side substitutability. However, an important advantage of the broadband market is that consumers' demand has zero mobility---- consumers can only order from providers which offer services at their residences. 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.[19] In the mean time, we cannot adopt traditional market definitions relying on the boundaries of geographical areas in which consumers choose products or services.

Our definition of a local market reflects the supply side consideration and 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

[19] However, consumer immobility can be an issue if a provider only covers part of a zip code instead of the entire zip code. As detailed in section 3.4, we alleviate this problem by selecting zip codes covering smaller geographical areas.

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. 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. "Physical" 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). "Strategic" sunk costs, including the loss of option value and the cost of switching consumers away from incumbent firms, are naturally associated with physical sunk costs. 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 of the central office,[20] 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

[20] 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).

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 most appropriate approximation of local markets in the broadband market.[21]

The FCC only requires that facilities-based providers report their presence in a given zip code. That means that all of the providers in data set will, at minimum, incur costs of laying out network facilities. There are, as discussed in section 2, other types of sunk entry costs such as consumers' switching costs, costs caused by incumbents preemptive behavior, and entrant's option value of waiting. It's likely that these remaining sunk costs will vary by type of firms and order of entry, and we will try to capture some of these costs by extension 2.

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,[22] 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

[21] Augereau, Greenstein, and Rysman (2005) 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.
[22] For example, Time-Warner America Online.

report the number of providers for each zip code in the United States. The 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.[23] Each provider is required to report its presence in a given zip code as long as it serves at least one customer in 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 advantage of this dataset is clear. The market of high-speed line providers is growing rapidly and there is significant entry and exit during the time span of the data. Moreover, 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 set departs from an "ideal" one [24] due to a few major restrictions resulted from the FCC's confidential agreements with the broadband providers. First, 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 only have a crude way to deal with this potential correlation, as shown in the county random effects model. Second, 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).[25] Third, small providers, many of whom serve sparsely populated areas,

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

[24] 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."

[25] 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.

are not required to report to FCC, potentially causing measurement errors in our econometric analysis.[26] 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). Lastly, 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.

To complement the main data, we merge in information from the 2000 Population Census based on zip code tabulation areas (ZCTAs).[27] Our measure of market size is the population in ZCTAs.[28] 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 Population Census data are also matched to the Zip Code Business Pattern (2000), which allows us to merge in the number of employee-based business establishments for each zip code. We use this variable divided by local population 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

[26] Small providers (with less than 250 high-speed lines) may provide information on a voluntary basis.
[27] 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.
[28] We could use the number of business establishments in the zip code as an alternative measure of market size. However, the size of population and the number of business establishments are highly correlated. In addition, the use of population provides a better comparison with BR who also use that same proxy for market size.

from the universe of 31913 zip codes in the United States.[29] 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.[30] 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 are concerned that providers serving such a zip code did not compete with each other.[31] Our selection criteria leave us with 14357 zip codes observations per period over 9 semi-annual time periods from December 1999 to December 2003.[32]

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 0.44 providers per market. Four years later, they averaged 1.73 providers per market. There is tremendous variation in the distribution of providers. In December 1999, 74% (number from table 2) 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.

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[29] 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).

[30] A typical zip code area in this category covers a radius less than 1 mile.

[31] 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.

[32] 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.

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.[33] On average, our zip code markets have a population of 1020 with a land area of 54 square miles.[34] 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. Around one-third of the population is over 60. Around 5% 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 167 business establishments per thousand population.[35]

4. RESULTS

A closer look at the data can give us an idea why a static framework without sunk costs 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

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[33] Prieger (2003) investigates whether there is unequal broadband availability in areas with high concentrations of poor, minority, or rural households. He identifies various demographic factors affecting the availability of broadband access.

[34] The population density is 188 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.

[35] Both distributions of population density and firm density are highly skewed to the right. For population density, the median is around 29; for firm density, the median is around 17. This is why we take log of both density variables and use the log form in the estimation.

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 static framework will generate a weighted average of the "true" entry threshold and a smaller, exit threshold----the market size that allows the n^{th} incumbent firm to remain in business. Therefore, the estimation results without sunk costs 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 framework without sunk costs will overestimate the entry threshold ratios most from the 1-3 provider category to the 4 firm category, especially in the later periods as incumbency dominates.

In reviewing the results, it is important to keep in mind how data limitations may affect our interpretation of the estimates. First, because we observe net entry and exit numbers and not the number of entrants and exits, we treat as equals markets where one firm enters and markets where three firms exit and four firms enter. Second, we treat each entrant as homogeneous even though they may be using different modes of service delivery, are independent firms or part of a regional or national entity, and may serve as few as 200 customers up to an undetermined upper-limit. Our data and model does not capture any heterogeneity along these lines. Third, the FCC lumps one to three providers in a single category for confidentiality reasons, and this prevents us from assessing firm conduct in progressing from local monopoly to local duopoly and on to local triopoly. We will make note of how these limitations alter our interpretations as we discuss our results.

4.1 Results of Our Baseline Model

Table 5 reports estimates from our baseline model, where sunk costs are incorporated. We will report the results from the BR model later for comparison. Note that each regression requires a normalization of the variance of the error term, and so we can only compare coefficient signs and significance but not magnitudes across time periods. Population size is a significant determinant of the number of providers operating in a zip code. Zip codes with a higher percentage of Native Americans discourage the presence of broadband providers, while a higher percentage of Asians raises the number of providers. Evidence on the impact of Black and Hispanic populations is mixed. Richer and better-educated populations attract more providers, while zip codes with larger households,[36] more females, and more senior citizens discourage them. Populations that rent or have longer commuting distances attract broadband services, while population that work from home have little impact and population with telephones has mixed impact. Rural areas attract fewer providers, while areas with more prosperous businesses activity, as measured by firm density, attract more. On the contrary, higher population density lowers the number of providers ---- we think this may be due to the high colinearity between population size and population density measures. Most of these coefficients are stable over time and statistically significant.

In table 5, the cutoff points μ_t^n and sunk costs SC_t are estimated with very good precision. Table 6a reports results calculated from the estimates of the coefficients, cutoff points, and sunk costs in table 5. Table 6a reports entry threshold, which is the market size necessary to support n firms in a market with net entry 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 3,492 people are necessary for a zip code area to support 1 to 3 providers in December

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

1999, while only 1,981 people are necessary in December 2003. Similarly, around 7,962 people are necessary to support 4 providers in December 1999 but only 4,179 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 7a reports entry thresholds derived from the model without the sunk costs of entry.[37] As we discussed earlier, we expect that the framework without sunk costs will underestimate entry thresholds by estimating a weighted average of entry and exit thresholds, especially for entry into the 1-3 firm category. The bias would increase later in the period as incumbents increased in proportion to the total number of firms. Table 7a confirms our expectations. Every threshold reported here is smaller than its counterpart in table 6a. By December 1999, the population necessary to support a 1-3 firm oligopoly was 2,349, while the baseline estimate was 3,492; by December 2003, the population necessary to support the same market structure was 204 rather than 1,981 as estimated in the baseline model. These patterns are the same for all other market structures. In other words, the framework without sunk costs 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.

[37] The coefficient estimates for the control variables in this no-sunk-cost model are very close to the baseline model, except that in this model the estimated effect of population increased much more rapidly over years. We suspect that this is because the population coefficient absorbs some of the ignored effects of entry costs in the framework without sunk costs.

4.2 Construction of Entry Threshold Ratios

Now we need to analyze the entry threshold ratios, from which we can infer changes in competitive conduct as a new firm enters the market. As discussed earlier, if $\frac{s_t^{n+1}}{s_t^n} = 1$ there is no change in competitive conduct in moving from n to $n+1$ firms in the zip code area.

The weakness in our data is that it does not distinguish between 1, 2, or 3 providers in a given zip code. As a result, we are not able to detect any change in competitive conduct in the 1 to 3 provider category. Luckily, the policy focus of the FCC is on whether a smaller, competitive provider can bring competition into the market place. For example, the 1996 Telecommunication Act subsidizes the entry of Competitive Local Exchange Carriers (CLECs), which mostly provide telephone and broadband services to small businesses. Given that in the broadband market the first two entrants are almost always the local cable company and the Incumbent Local Exchange Carrier (ILEC), we know that from the 3rd entrant on the new entrant must be a smaller, competitive provider. So the change in competitive conduct outside of the 1-3 provider category is still relevant for policy: would the fourth entrant make any difference in the competitive conduct of local broad markets? If yes, then the policy of subsidizing multiple entries seems solid. If no, then the FCC does not need to subsidize additional entry beyond the third, as we know that subsidies often distort economic incentives, because as few as 3 providers are sufficient to create a competitive environment.

To evaluate competitive conduct, we exploit some supplemental information provided by the FCC. Their semi-annual reports include the distribution of 1-, 2- and 3-provider markets at the national level in every period, allowing us to develop bounds for the relevant market sizes to support entry in the 1 to 3 provider category. Denote S_entry^{1-3} as the necessary market size to support the entry of one, two, or three firms, and let p^n be the percentage of providers in the n^{th} category ($n = 1, 2, or\ 3$) among all 1 to 3 firm oligopoly market.[38] On average, S_entry^{1-3} is an overestimate of the market size necessary to support an entrant but an underestimate of the market size necessary to support three entrants. Given that s^n is the average market size supporting entry of the n^{th} firm, we can write S_entry^{1-3} as:

$$(12) \qquad S\_entry^{1-3} = s^1 * p^1 + 2s^2 * p^2 + 3s^3 * p^3$$

Note the above equation is an ad hoc approximation only to get around our data limitations. As such, these results should be viewed as suggestive due to the measurement error in true local p^n.

Note that it takes at least the same market size to support another firm, and so we can assume that $s^1 \leq s^2 \leq s^3$. Under this assumption, equation (12) becomes

$$(13) \qquad S\_entry^{1-3} \geq s^1 * p^1 + s^2 * p^2 + s^3 * p^3 \geq s^1 \left(p^1 + p^2 + p^3 \right) = s^1$$

and

$$(14) \qquad S\_entry^{1-3} = s^1 * p^1 + 2s^2 * p^2 + 3s^3 * p^3 \leq s^3 \left(p^1 + 2p^2 + 3p^3 \right)$$

Following (13) and (14), we can derive an upper bound for s^1 and a lower bound for s^3:

$$(15) \qquad s^1 \leq S\_entry^{1-3}$$

$$(16) \qquad s^3 \geq \frac{S\_entry^{1-3}}{\left(p^1 + 2p^2 + 3p^3 \right)}.$$

Given these bounds, we can further derive a lower bound for $\frac{s^4}{s^1}$ and an upper bound for $\frac{s^4}{s^3}$:

$$(17) \qquad \frac{s^4}{s^1} \geq \frac{S\_entry^4 / 4}{S\_entry^{1-3}}$$

$$(18) \qquad \frac{s^4}{s^3} \leq \frac{S\_entry^4 / 4}{S\_entry^{1-3} / \left(p^1 + 2p^2 + 3p^3 \right)}.$$

[38] We omit the t subscript in this discussion to simplify notion.

We can interpret the lower bound for $\frac{s^4}{s^1}$ as the lower bound of the average change in competitive conduct when the 4th firm enters a monopoly market[39] and the upper bound for $\frac{s_4}{s_3}$ as the upper bound of the average change in competitive conduct when the 4th firm enters a three-firm oligopoly market. Combining the two bounds, we can infer the change of competitive conduct when the fourth firm enters a one to three firm oligopoly market structure.

Tables 7a and 7b report entry threshold ratios for our baseline model and the no-sunk-costs model, respectively. As shown in both table 7a and 7b, when $n > 4$, $\frac{s^{n+1}}{s^n}$ is close to unity with only slight increases over time, suggesting that competitive conduct is stable when market structure goes beyond four firms. These ratios are slightly below one, suggesting that some sort of product/cost differentiation is involved in the new entry.

However, the two models paint drastically different pictures pertaining to the entry of the 4th firm. In the absence of sunk costs, table 7b shows rising values for $\frac{s^4}{s^1}\,\mathit{lower\ bound}$ and $\frac{s^4}{s^3}\,\mathit{upper\ bound}$. This implies that entry into a 1-3 firm oligopoly market gets progressively more difficult over time. In December 1999, competitive conduct changes only modestly as the 4th firm is added. By December 2003, it takes at least 3.4 times the monopoly market size and as much as 6.8 times the market size inducing the third entrant to support entry of the 4th firm. Incorporating sunk costs in table 7a, however, we find only small rising deviations from unity for $\frac{s^4}{s^3}\,\mathit{upper\ bound}$. As $\frac{s_4}{s_3}$ is theoretically bounded above unity, these upper bounds hint that the competitive conduct from a 1-3 firm oligopoly to a 4-firm market

[39] This happens when three firms enter a monopoly market concurrently.

changed only slightly over time.[40] 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 in concluding that the fringe players from the 4th firm on have little effect on the competitive conduct of the broadband market.

Figure 4 illustrate the comparison of the results from the two models, without or with sunk costs of entry. Note that we use $\frac{s^4}{s^3}$ *upper bound* as the first data point for every time period and the vertical axes of the left and right panel use different scale to be able to see the variation of entry threshold ratios in the right panel. The left panel shows much more dramatic change in competitive conduct as the fourth firm enters than the right panel does. Beyond the fourth firm, both panels suggest that the entry conditions stabilize. Back to the questions we ask in the beginning: Does the fourth entrant make any difference in the competitive conduct of a local broadband market? The answer is clearly positive in light of the findings in the left panel. However, the right panel produces the opposite answer, which indicates that he change in competitive conduct must have occurred before the arrival of the fourth firm. The policy implication of this answer is significant in the broadband market: given most local markets are already served by a cable company and an ILEC, subsidizing just another entrant might suffice to bring in effective competition.

Is the industry becoming increasing competitive over time? In table 8, we test formally for systematic differences in entry threshold ratios over time under our baseline model. 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 $\frac{s_t^n}{s_t^{n-1}} = \frac{s_{t-1}^n}{s_{t-1}^{n-1}}$, we constrain μ_t^n 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

[40] The lower bound for $\frac{s^4}{s^1}$ is less informative as the numbers are well below one.

change shows some, if not huge, economical significance as shown in table 7a, 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 almost 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?

Tables 9a and 9b report results from the first extension of our baseline model which allows entry costs to vary with the order of entry. Recall that our baseline model is the most restrictive model, assuming $SC_t^{1-3} = SC_t^4 = SC_t^5 = SC_t^6 = SC_t^7$. In table 9a, we allow the sunk costs of entrants into the 1-3 firm oligopoly market to be different from the later entrants. In table 9b, 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_t^n. 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.

Table 9c reports likelihood ratio tests for the null hypotheses $SC_t^{1-3} = SC_t^4 = SC_t^5 = SC_t^6 = SC_t^7$ and $SC_t^{1-3} \neq SC_t^4 = SC_t^5 = SC_t^6 = SC_t^7$. The test results show that we can reject the null hypotheses $SC_t^{1-3} = SC_t^4 = SC_t^5 = SC_t^6 = SC_t^7$ but cannot reject $SC_t^{1-3} \neq SC_t^4 = SC_t^5 = SC_t^6 = SC_t^7$ for these early periods. These test results support the findings in table 9a and 9b, 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 10a, 10b, and 10c reports results from the second extension of our baseline model, which allows county-level random effects. As table 10a shows, the variance of the country-specific error η_{county} is estimated with high precision. Comparing table 5 and table 10a, we can see that controlling for random effects greatly improves the log likelihood. Though table 10a hints at the importance of allowing profitability of adjacent markets to be correlated, table 10b and 10c suggests otherwise. In tables 10b and 10c, the estimated entry thresholds and entry threshold ratios change little compared to tables 6a and 7a. In fact, all the structural parameters and their variances are similar with or without county-level random effects. 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 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 4th 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 fourth entrant has little effect on competitive conduct in the local broadband market.

The results we have derived, however, do have nontrivial flaws. First, we include sunk costs in a model without real dynamics. Second, the data we use lump 1 to 3 providers in the same category so we cannot capture the actions inside this category. The misspecification resulted from these flaws does restrict us from making policy-relevant suggestions. For example, we cannot advise on a subsidy policy which reduces the sunk cost of entry with the goal of encouraging the arrival of more broadband providers. This said, our work improves upon the original static entry framework by distinguishing between entrants and incumbents and sheds highlight on the importance of sunk costs in determining entry conditions and inferences about firm conduct.

Some may argue that short-term dynamics such as learning or adjustment costs may be the driving force in shaping the short-run market structure in a rapidly evolving industry. For example, preemption incentives may lead to early entry in the emerging stages of an industry, or firms overestimate profitability before entry and decide to exit after learning the market conditions. We have no objection to this view, however, we think that incorporating sunk costs is the very first step in modeling entry and exit before allowing for any short-term dynamics. If our empirical model had produced dramatically different or inconsistent estimates of entry behaviors in the various stages of the industry in study, then we should have started to investigate what is behind the differences or inconsistencies.

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

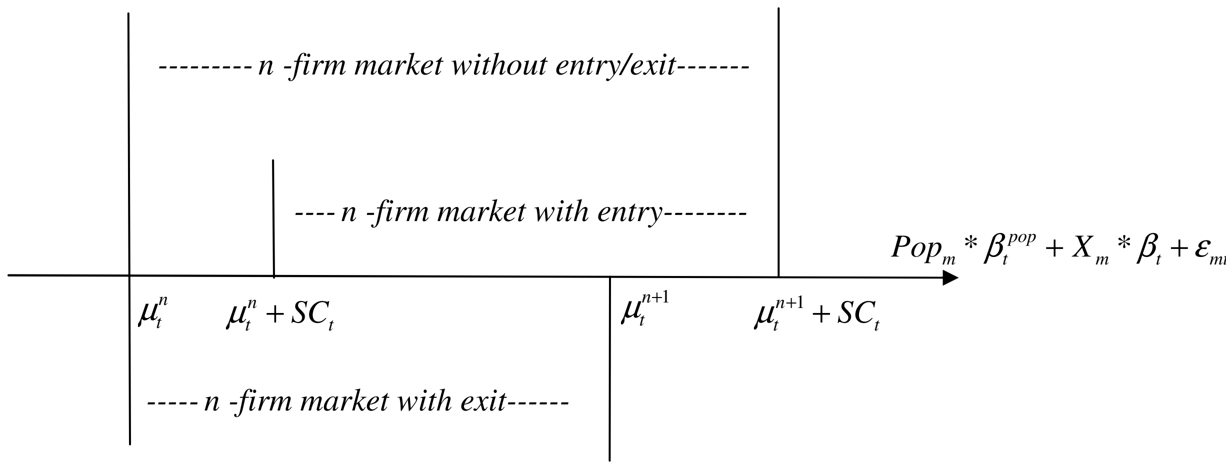
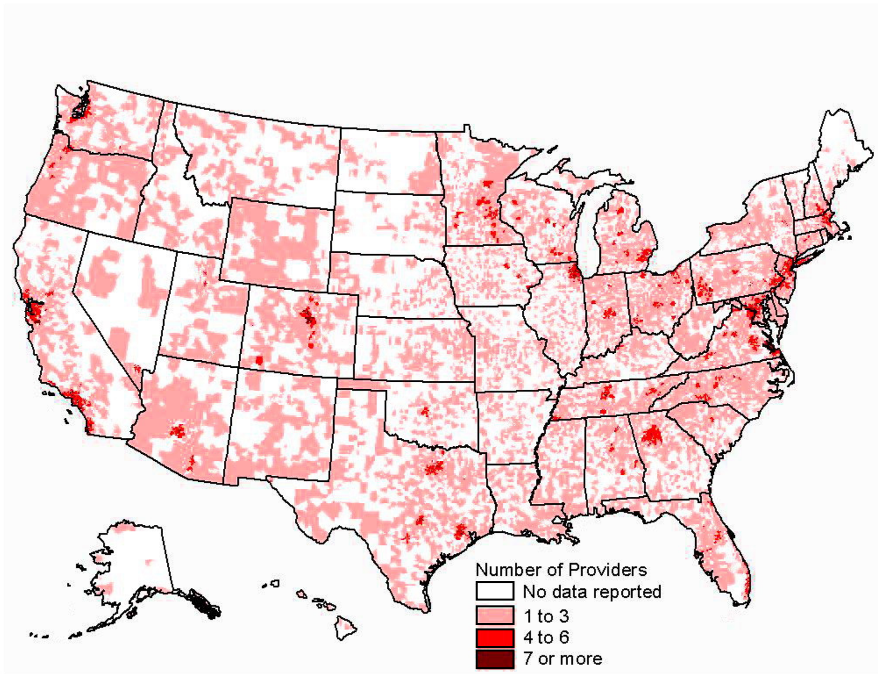


Figure 2 Broadband Distribution by Number of Providers per Zip Code

December 1999



December 2003

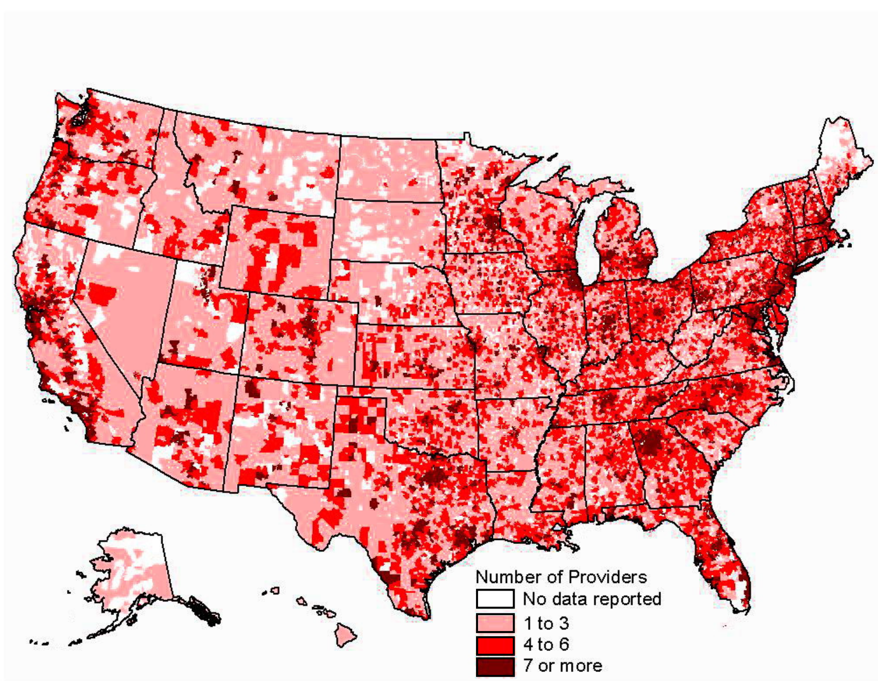


Table 1 Summary Statistics on Firm Entry, Exit, and Incumbency

Variable	Mean	Standard Error	Min	Max
Number of providers in a zip code market				
Dec 1999	0.440	0.769	0	9
Jun 2000	0.595	0.876	0	11
Dec 2000	0.801	1.055	0	15
Jun 2001	0.961	1.126	0	16
Dec 2001	1.016	1.147	0	14
Jun 2002	1.207	1.242	0	16
Dec 2002	1.386	1.277	0	17
Jun 2003	1.565	1.377	0	16
Dec 2003	1.726	1.425	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	0.885	0.318	0	1

Note: FCC lumps 1 to 3 providers into one category but provides percentage of zip codes with 1, 2, and 3 providers in their semiannual report. We use this information to calculate the adjusted mean of number of providers in a zip code market in each time period.

Table 2 **Percentage of Zip Codes with n Firms**

	Dec99	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
$n=0$	73.90	65.80	57.73	51.71	49.66	42.33	35.60	30.74	26.93
$n=1-3$	25.77	33.65	40.76	46.30	47.93	53.94	59.71	61.86	63.66
$n=4$	0.17	0.30	0.91	1.25	1.55	2.39	3.09	4.85	6.03
$n=5$	0.06	0.08	0.24	0.31	0.40	0.63	0.81	1.46	2.00
$n=6$	0.04	0.06	0.13	0.16	0.15	0.28	0.26	0.39	0.56
$n \geq 7$	0.06	0.11	0.24	0.27	0.31	0.43	0.54	0.70	0.81
$N=14357$	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	1.020	0.743	0.001	2.733
% Black	% population: African Americans	0.050	0.141	0	1
% Hispanic	% population: Hispanics	0.037	0.103	0	1
% Native	% population: Native American	0.023	0.110	0	1
% Asian	% population: Asians	0.004	0.024	0	1
m_income	Household median income	35443	13554	0	200k
% college	% population over 25 with some college education	0.383	0.156	0	1
hh_size	Average household size	2.564	0.341	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
land area	square miles of land area	53.771	74.228	0.002	1033.6
pop density	# people per square mile	188.081	539.604	2.607	5221.3
firm density	# establishments per thousand of population	166.563	7383.319	0.497	760k

*: 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
$n=1-3$	**31.71**	**24.97**	**26.16**	**15.13**	**17.17**	**15.05**	**10.56**	**7.46**
$n=4$	79.07	88.46	71.51	58.11	62.10	53.95	58.76	42.15
$n=5$	72.73	91.43	75.00	58.62	70.33	60.34	70.00	57.49
$n=6$	77.78	83.33	52.17	59.09	60.00	50.00	76.79	67.90
$n\geq 7$	62.50	55.88	28.21	27.27	37.10	25.97	24.75	18.97
% of n -firm Markets with No Net Entry/Exit								
Markets with								
$n=0$	96.08	96.34	88.20	89.52	95.41	93.66	94.56	96.43
$n=1-3$	**68.14**	**74.91**	**72.61**	**83.56**	**82.13**	**83.52**	**88.54**	**90.97**
$n=4$	16.28	10.00	22.91	34.23	33.82	38.83	37.50	51.62
$n=5$	18.18	5.71	15.91	25.86	25.27	33.62	26.19	36.59
$n=6$	11.11	11.11	21.74	18.18	27.50	39.47	23.21	28.40
$n\geq 7$	37.50	44.12	71.79	72.73	62.90	74.03	75.25	81.03

Note: this table does not report the percentage of n -firm markets with net exit, but readers can easily infer the numbers. For example, in Jun 2000 31.71% of 1-3 firm markets have experienced net entry and 68.14% have experienced neither net entry nor net exit, therefore only 0.15% of these markets have experienced net exit.

Table 5 MLE Results for the Baseline Model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
pop/1000	0.429	0.481	0.695	0.550	0.602	0.621	0.623	0.617
	(0.020)***	(0.020)***	(0.019)***	(0.020)***	(0.022)***	(0.022)***	(0.022)***	(0.024)***
% Black	-0.438	0.194	0.153	0.010	0.234	0.331	-0.082	0.152
	(0.121)***	(0.093)**	(0.095)	(0.102)	(0.105)**	(0.093)***	(0.096)	(0.103)
% Hispanic	-0.392	0.218	0.356	-0.042	-0.486	-0.073	-0.249	-0.473
	(0.182)**	(0.132)	(0.142)**	(0.152)	(0.128)***	(0.145)	(0.147)*	(0.165)***
% Native	-0.417	-0.866	-0.493	-0.252	-0.262	0.004	-0.101	0.014
	(0.223)*	(0.230)***	(0.159)***	(0.134)*	(0.152)*	(0.163)	(0.167)	(0.153)
% Asian	0.353	1.783	1.061	0.827	1.752	0.841	0.653	0.234
	(0.462)	(0.325)***	(0.346)***	(0.359)**	(0.322)***	(0.424)**	(0.471)	(0.535)
ln(m_incom)	0.248	0.401	0.420	0.229	0.435	0.289	0.366	0.384
	(0.051)***	(0.048)***	(0.040)***	(0.053)***	(0.045)***	(0.044)***	(0.043)***	(0.046)***
% college	0.820	0.074	0.808	0.344	0.057	0.314	0.352	-0.076
	(0.114)***	(0.113)	(0.098)***	(0.111)***	(0.103)	(0.107)***	(0.101)***	(0.110)
hh_size	-0.178	-0.179	-0.141	-0.139	-0.172	-0.160	-0.054	-0.052
	(0.063)***	(0.051)***	(0.047)***	(0.049)***	(0.052)***	(0.053)***	(0.052)	(0.065)
% female	-0.749	-0.683	-1.199	-1.055	-1.300	-0.940	-0.866	-0.742
	(0.308)**	(0.280)**	(0.286)***	(0.299)***	(0.270)***	(0.264)***	(0.287)***	(0.344)**
% senior	-0.253	-0.618	-0.028	-0.295	-0.529	-0.202	0.082	-0.465
	(0.213)	(0.197)***	(0.187)	(0.200)	(0.199)***	(0.204)	(0.202)	(0.236)**
% w_home	0.204	-0.165	0.368	0.144	0.327	0.378	0.150	0.393
	(0.256)	(0.251)	(0.254)	(0.254)	(0.240)	(0.275)	(0.276)	(0.315)
% long_cmu	0.638	0.516	-0.027	0.345	0.129	0.428	0.249	-0.167
	(0.118)***	(0.113)***	(0.101)	(0.107)***	(0.109)	(0.103)***	(0.106)**	(0.116)

% rent	1.085	0.368	0.902	0.603	0.521	0.692	0.691	0.644
	(0.135)***	(0.119)***	(0.113)***	(0.126)***	(0.115)***	(0.113)***	(0.113)***	(0.124)***
% phone	0.626	0.131	-0.334	-0.398	0.028	0.670	0.601	0.681
	(0.330)*	(0.318)	(0.270)	(0.259)***	(0.275)	(0.306)**	(0.280)**	(0.334)**
% rural	-0.113	-0.423	-0.349	-0.341	-0.408	-0.419	-0.496	-0.359
	(0.076)	(0.071)***	(0.067)***	(0.073)***	(0.068)***	(0.066)***	(0.066)***	(0.071)***
ln(pop_dsty)	0.004	-0.023	-0.136	-0.045	-0.073	-0.128	-0.136	-0.119
	(0.014)	(0.014)*	(0.012)***	(0.013)***	(0.013)***	(0.013)***	(0.013)***	(0.014)***
ln(firm_dsty)	0.117	0.060	0.138	0.149	0.097	0.106	0.106	0.082
	(0.018)***	(0.016)***	(0.016)***	(0.016)***	(0.017)***	(0.017)***	(0.017)***	(0.018)***
μ^{1-3}	2.438	2.283	2.943	0.756	2.033	1.475	2.234	2.081
	(0.516)***	(0.507)***	(0.401)***	(0.522)	(0.448)***	(0.422)***	(0.426)***	(0.448)***
μ^4	4.357	3.817	4.833	2.289	3.601	3.155	3.603	3.436
	(0.475)***	(0.486)***	(0.384)***	(0.516)***	(0.438)***	(0.416)***	(0.421)***	(0.443)***
μ^5	4.740	4.266	5.320	2.775	4.095	3.681	4.147	3.937
	(0.451)***	(0.472)***	(0.373)***	(0.511)***	(0.431)***	(0.409)***	(0.418)***	(0.444)***
μ^6	4.913	4.528	5.615	3.089	4.421	4.033	4.580	4.381
	(0.499)***	(0.488)***	(0.389)***	(0.521)***	(0.439)***	(0.409)***	(0.416)***	(0.446)***
μ^7	5.135	4.737	5.857	3.345	4.689	4.224	4.846	4.691
	(0.551)***	(0.535)***	(0.432)***	(0.549)***	(0.469)***	(0.448)***	(0.447)***	(0.469)***
SC_t	2.202	2.374	1.678	2.034	2.374	2.239	2.479	2.695
	(0.032)***	(0.034)***	(0.027)***	(0.028)***	(0.033)***	(0.031)***	(0.033)***	(0.035)***
$\ln L$	-5537.3	-5868.2	-6962.8	-6261.2	-6033.2	-6186.2	-6324.3	-5776.4

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: the Baseline Model

Population (in thousands) Needed to Support n Firms with Net Entry								
	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
$n = 1 - 3$	3.492	3.010	2.055	2.695	2.166	1.884	1.922	1.981
$n = 4$	7.962	6.200	4.774	5.483	4.770	4.588	4.119	4.179
$n = 5$	8.855	7.133	5.473	6.368	5.590	5.434	4.992	4.991
$n = 6$	9.258	7.680	5.899	6.939	6.131	6.000	5.687	5.711
$n \geq 7$	9.775	8.114	6.247	7.406	6.575	6.308	6.114	6.215

Note: We calculate entry thresholds (Table 6a) and entry threshold ratios (Table 7a) 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 7a, 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 tables 6b, 7b, 10b and 10c.

Table 6b Entry Thresholds: No Sunk Costs

Population (in thousands) Necessary to Support n firms									
	Dec99	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
$n = 1 - 3$	2.349	1.790	1.347	1.074	0.993	0.742	0.521	0.346	0.204
$n = 4$	6.888	6.049	4.873	4.033	3.829	3.454	3.238	2.942	2.756
$n = 5$	7.480	6.670	5.539	4.614	4.420	4.032	3.831	3.576	3.387
$n = 6$	7.864	6.949	5.892	4.910	4.755	4.358	4.172	3.996	3.837
$n \geq 7$	8.263	7.271	6.164	5.150	4.960	4.603	4.356	4.196	4.073

Figure 3 Entry Thresholds over Time

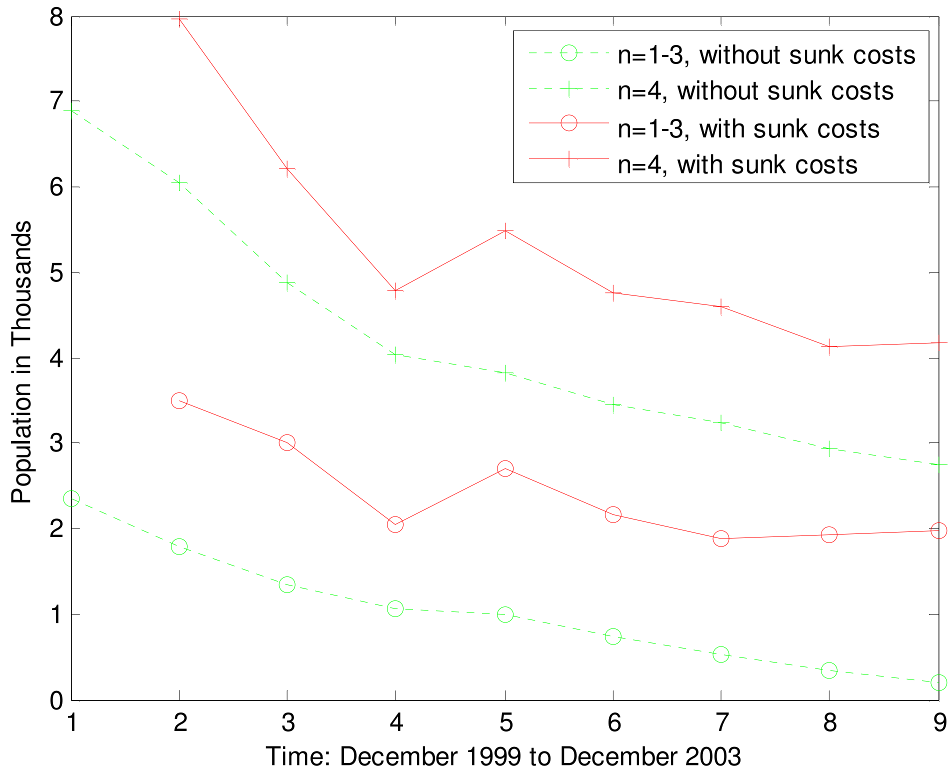


Table 7a Entry Threshold Ratios: the Baseline Model

	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
$\frac{s^4}{s^1}$ *lower bound*	**0.570**	**0.515**	**0.581**	**0.509**	**0.550**	**0.609**	**0.536**	**0.527**
$\frac{s^4}{s^3}$ *upper bound*	**0.960**	**0.913**	**1.080**	**0.952**	**1.042**	**1.178**	**1.044**	**1.055**
$\frac{s^5}{s^4}$	0.890	0.920	0.917	0.929	0.937	0.948	0.969	0.955
$\frac{s^6}{s^5}$	0.871	0.897	0.898	0.908	0.914	0.920	0.949	0.954
$\frac{s^7}{s^6}$	0.905	0.906	0.908	0.915	0.919	0.901	0.921	0.933

Table 7b Entry Threshold Ratios: No Sunk Costs

	Dec99	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
$\frac{s^4}{s^1}$ *lower bound*	**0.733**	**0.845**	**0.904**	**0.939**	**0.964**	**1.164**	**1.554**	**2.126**	**3.382**
$\frac{s^4}{s^3}$ *upper bound*	**1.204**	**1.423**	**1.604**	**1.745**	**1.803**	**2.203**	**3.005**	**4.145**	**6.763**
$\frac{s^5}{s^4}$	0.869	0.882	0.909	0.915	0.924	0.934	0.946	0.972	0.983
$\frac{s^6}{s^5}$	0.876	0.868	0.886	0.887	0.896	0.901	0.907	0.931	0.944
$\frac{s^7}{s^6}$	0.901	0.897	0.897	0.899	0.894	0.905	0.895	0.900	0.910

Figure 4 Entry Threshold Ratios over Time

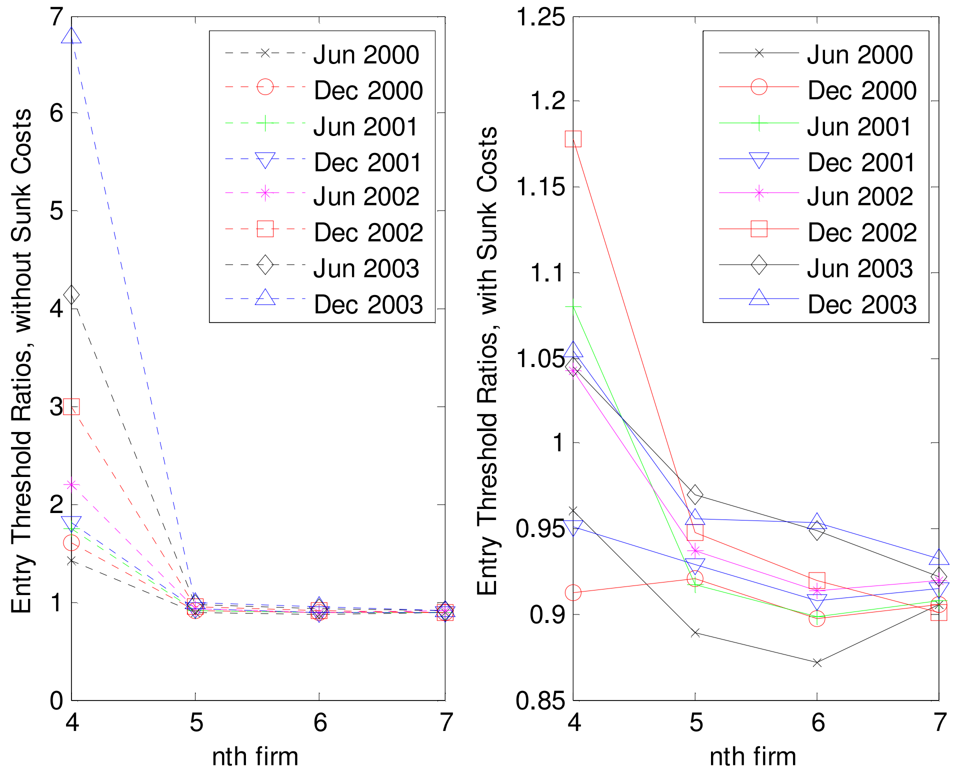


Table 8 Likelihood Ratio Tests for Constant Entry Threshold Ratios over Time

	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
Test for $\frac{s_t^4}{s_t^1}\,lower\ bound = \frac{s_{t-1}^4}{s_{t-1}^1}\,lower\ bound$	0.043	17.513***	9.791**	4.721**	1.520	0.163	0.801
Test for $\frac{s_t^4}{s_t^3}\,upper\ bound = \frac{s_{t-1}^4}{s_{t-1}^3}\,upper\ bound$	5.373**	93.442***	28.118***	32.117***	47.178***	23.982***	0.054
Test for $\frac{s_t^5}{s_t^4} = \frac{s_{t-1}^5}{s_{t-1}^4}$	5.941**	3.928**	0.120	3.001*	0.833	10.918***	0.547
Test for $\frac{s_t^6}{s_t^5} = \frac{s_{t-1}^6}{s_{t-1}^5}$	4.818**	5.783**	0.318	2.482	0.281	12.839***	1.227
Test for $\frac{s_t^7}{s_t^6} = \frac{s_{t-1}^7}{s_{t-1}^6}$	0.807	5.233**	0.328	1.855	1.109	8.689***	2.595

Table 9a **MLE Results: Extension 1,** $SC_t^{1-3} \neq SC_t^4 = SC_t^5 = SC_t^6 = SC_t^7$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
SC_t^{1-3}	2.196	2.367	1.659	2.032	2.370	2.244	2.494	2.876
	(0.033)***	(0.034)***	(0.028)***	(0.029)***	(0.034)***	(0.033)***	(0.036)***	(0.042)***
SC_t^4	2.532	2.684	1.923	2.050	2.399	2.220	2.429	2.404
	(0.240)***	(0.194)***	(0.100)***	(0.085)***	(0.088)***	(0.066)***	(0.065)***	(0.055)***
$\ln L$	-5536.3	-5867.0	-6959.2	-6261.2	-6033.1	-6186.1.6	-6323.9	-5750.2

Table 9b **MLE Results: Extension 1,** $SC_t^{1-3} \neq SC_t^4 \neq SC_t^5 = SC_t^6 = SC_t^7$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
SC_t^{1-3}	2.196	2.367	1.658	2.032	2.369	2.243	2.492	2.876
	(0.033)***	(0.034)***	(0.028)***	(0.029)***	(0.034)***	(0.033)***	(0.036)***	(0.042)***
SC_t^4	2.534	2.614	1.858	2.026	2.362	2.188	2.380	2.402
	(0.242)***	(0.209)***	(0.102)***	(0.087)***	(0.091)***	(0.067)***	(0.068)***	(0.056)***
SC_t^5	2.531	2.776	2.112	2.130	2.479	2.305	2.538	2.406
	(0314)***	(0.244)***	(0.133)***	(0.120)***	(0.119)***	(0.094)***	(0.086)***	(0.072)***
$\ln L$	-5536.3	-5866.7	-6956.2	-6260.6	-6032.5	-6185.0	-6321.8	-5750.2

Table 9c **Likelihood Ratio Tests for Entry Costs Proportionality**

	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
Test for $SC_t^{1-3} = SC_t^4 = SC_t^5 = SC_t^6 = SC_t^7$	1.974	2.834*	7.147***	0.100	0.160	0.178	0.817	52.310***
Test for $SC_t^{1-3} \neq SC_t^4 = SC_t^5 = SC_t^6 = SC_t^7$	0.016	0.600	5.970**	1.112	1.349	2.332	4.046**	0.006

Table 10a 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
$\sigma^2_{county,t}$	0.864	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)***
$\ln L$	-4950.9	-5585.6	-6762.5	-6022.6	-5941.2	-6094.2	-6237.7	-5686.0

Table 10b 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 10c Entry Threshold Ratios: Extension 2, Allowing County-level Random Effects

	Jun00	Dec00	Jun01	Dec01	Jun02	Dec02	Jun03	Dec03
$\frac{s^4}{s^1}$ *lower bound*	0.554	0.530	0.590	0.511	0.557	0.616	0.545	0.536
$\frac{s^4}{s^3}$ *upper bound*	**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