Who thinks about the competition?

Managerial ability and strategic entry in US local telephone markets*

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ABSTRACT

We examine US local telephone markets shortly after the Telecommunications Act of 1996. The data suggest that older, better educated managers tend to enter markets with fewer competitors. This motivates a structural econometric model based on behavioral game theory that allows heterogeneity in managers' ability to conjecture competitor behavior. We find that manager characteristics are key determinants in managerial ability. This estimate of ability predicts out-of-sample success. Also, the measured level of ability rises following a shakeout. Comparing our model and a Bayesian Nash equilibrium model suggests that our behavioral assumptions appear most relevant early in the industry's life cycle.

Keywords: behavioral industrial organization, cognitive hierarchy, entry games, CLECs, local telephone competition

JEL Classification: D03, L2, L96

1) Introduction

Managers make decisions. Sometimes these decisions are made without full information, sometimes they are short-sighted, and sometimes they are brilliant. But all in all, the success of a company chiefly lies in the quality of decisions made by its management. This is why CEO succession is a common *Wall Street Journal* headline. Thus far, however, most empirical economic models have treated firms as black boxes that make purely rational decisions. While empirical models allow heterogeneity in consumer preferences, firm attributes, costs, and market characteristics, they have generally failed to recognize variance in managers' abilities to understand rival firms' strategic behavior.

The aim of this project is to understand the incidence of heterogeneity in management ability in a new industry. The passage of the *Telecommunications Act of 1996* opened the competitive local telecommunications industry in the United States. Prior to this act, the market had been dominated by the incumbent local exchange carriers, or "Baby Bells." While widespread competition is still not the norm, the 1996 Act led to substantial entry. The entrants (known as competitive local exchange carriers, or CLECs) varied substantially in size, management, and telecommunications experience. Their managers chose which cities and towns the firms should enter following the opening of the market.

The early years of this industry provide an ideal setting for exploring heterogeneity in the strategic ability of managers. Manager experience was heterogeneous, the industry had not yet experienced a shakeout of the lower-quality firms, and industry norms were still developing. More importantly, and in contrast to many existing models of firm behavior in new industries that emphasize cost and production heterogeneity (e.g., Klepper 2002; Holmes and Schmitz 1995), our data suggest a strong correlation between manager characteristics and competitive considerations. Our descriptive analysis, which characterizes the entry decisions of facilities-based CLECs in 234 midsize US markets with populations between 100,000 and 1,000,000 as of the 2000 Census, reveals that older CEOs and CEOs who attended top undergraduate institutions tended to enter markets with fewer competitors.

We develop a model that puts a useful structure on this correlation. The model we use draws on laboratory evidence of iterated decision-making in simultaneous games. In particular, numerous laboratory experiments show that people are heterogeneous in the strategies they use to play games. Simply, some people are better at playing games than others. While "better" has several dimensions, much of the laboratory research emphasizes heterogeneity in the ability of players to correctly conjecture competitor behavior. This heterogeneity does not appear to be random; rather, the observed behavior is consistent with an iterative decision process in which some participants do not consider the other players, others consider the other players but do not consider that the other players will consider them, etc. (Camerer 2003). Because a key application of game theory in economics is to understand the behavior of firms in competitive situations, the experimental evidence suggests that some managers may be better at making conjectures about competitor behavior than others.

Several related models allow for heterogeneity in the ability of players to correctly conjecture competitor behavior in entry games, including quantal response equilibrium (e.g., McKelvey and Palfrey 1995), level-k thinking (e.g., Costa-Gomes and Crawford 2006), and cognitive hierarchy (e.g., Camerer, Ho, and Chong 2004). For our purposes, cognitive hierarchy (henceforth CH) models the heterogeneity in an especially useful way because it includes a parameter that unambiguously identifies players as being better at playing the game. This parameter generates a type distribution for strategic ability. In particular, players have types 0 to

K. A type 0 player does not consider the competition. A type 1 player acts as if all other players are type 0. A type 2 player acts as if all other players are distributed between type 0 and type 1. And a type *k* player acts as if all other players are distributed between type 0 and type *k*-1. Therefore, higher types are better able to conjecture competitor behavior and consequently are less likely to regret their decisions once all decisions are observed. Unlike games featuring multiple Nash equilibria with fully rational players, this hierarchy yields a unique solution. This unique solution enables us to determine the identities of entrants as well as to associate entry decisions with manager and firm characteristics. Relying on prior research, we interpret the hierarchy as a measure of strategic ability.[1] This interpretation allows us to examine which CEO characteristics are determinants of strategic ability. Empirically, the players identified as better at playing the game will be those that choose to enter markets with few competitors and choose not to enter markets with many competitors.

Our estimates yield four core results. First, although journalists like to play up unobservable characteristics such as charisma and leadership as driving CEO success, the traditional wisdom of reviewing a manager's curriculum vitae works. Older, better educated managers tend to enter markets with fewer competitors. Second, our measure of strategic ability predicts outcomes outside our estimation window: Firms with managers of higher estimated ability are more likely to stay in business and, conditional on survival, have higher revenue. In short, smarter firms make smarter moves and succeed. Third, comparing results across years, we find that the measured level of ability is substantially higher in 2002 than in 1998. Fourth, our model fits the 1998 data much better than a Bayesian Nash equilibrium model with fully rational

[1] Camerer and Johnson (2004) track how long subjects looked at competitor payoffs and find that measured strategic ability is positively correlated with time spent looking at competitor payoffs. Bosch-Domenech et al. (2002) ask subjects in a beauty contest game to explain their choices and find that people explain their actions with logic based on thinking steps.

players, specifically Seim's (2006) model. In contrast, in 2002 our model performs only slightly better than Seim's. Given that there was a shakeout in 2001, we interpret these latter two results as supporting evidence for an evolution towards the long-run equilibrium outcome assumed in much of the existing simultaneous entry literature (e.g., Greenstein and Mazzeo 2006, p. 337). Combined with several industry facts and the existing laboratory research, these four results suggest internal and external validity for our "behavioral" model, particularly early in this industry's life cycle

Next, we provide details of the CLEC environment that motivate our choice to apply the CH model and discuss the relevant literature. The data, model, and results follow. We conclude with a discussion of limitations and the general implications of our results.

2) Background and Literature

In this section, we review four distinct topics that put our study in context.

Local Telephone Competition

Between the *Kingsbury Commitment* in 1913 and the *Telecommunications Act of 1996*, there was little competition in local telecommunications in the United States. The 1996 Act opened up local competition, primarily by barring state regulators from denying entrants the right to compete, by forcing incumbent carriers to allow competitors to interconnect, and by forcing incumbent carriers to allow entrants access to many of their facilities and rights-of-way (Crandall 2005). It took until 1998 for entry to be observed on any scale, and by 2000 there were 98 CLECs operating in a total of 190 different mid-sized US cities.[2] A shakeout followed, and at the nadir 64 CLECs were operating in 195 locations. Of the CLECs that were licensed to enter these

[2] We focus on mid-sized cities (with population between 100,000 and 1,000,000) for three reasons. First, smaller places are typically non-urban areas that contain too few customers to attract CLECs. Second, larger cities often encompass several sub-markets, so it is difficult to determine the existence and scope of strategic interactions among entrants. Finally, a handful of larger markets had local telephone competition prior to the 1996 Telecom Act.

mid-sized markets in 1998, just 42% survived independently through 2002. Thus, while many firms exited, the number of markets served by the remaining firms increased.

Both Goldstein (2005) and Crandall (2005) provide detailed histories of telecommunications competition following the 1996 Act. Both emphasize that many CLECs entered the same markets and ended up competing fiercely with each other. For example, Goldstein (2005, p. 116) writes that it is "likely that the CAPs [CLECs] did not count on each other's dividing the take" and that this led to lower than expected revenues and large losses. Crandall (2005, p. 39) notes that "a major problem for the new competitors is their proliferation in a given market." Their assessments suggest that the ability to conjecture the number of competitors that will enter a market is an important determinant of success.

In addition to this anecdotal support for our modeling framework, our data suggest an intriguing link between considering the competition and management characteristics. Figure 1 presents data from 1998 and shows that being the only player in the market appeared to be systematically correlated with a manager's age, experience, undergraduate institution quality, and degree field. We provide descriptive regression analysis supporting this link between manager characteristics and the level of competition after describing the dataset in Section 3.

This evidence suggests that managers with different personal backgrounds tend to act differently and that the difference is consistent with more able managers being better at guessing competitor behavior. Therefore, we apply a model of heterogeneity in ability that matches manager characteristics to strategic entry decisions.[3]

We conclude the section on local telephone competition by noting that our paper is not the first to examine competition in these markets. Other papers on local telephone competition

[3] Of course, we acknowledge that heterogeneity in the ability to conjecture competitor behavior is not the only possible explanation for these correlations. We discuss alternative explanations below and argue that a model of heterogeneous strategic ability is most consistent with our data.

include Economides, Seim, and Viard (2008) on the consumer welfare effects of the increase in local phone competition between 1999 and 2003 in New York state, Ackerberg et al (2009) on low-income subsidies after the 1996 Act, and Mini (2001) and Alexander and Feinberg (2004) on the incumbent attempts to restrict entry. Mobius (2001) also discusses behavioral biases in this industry (in the early 20th century) by arguing that myopic consumer behavior (in the presence of network externalities) explains patterns in local telephone competition. Closest to our work is Greenstein and Mazzeo (2006), who examine CLEC entry decisions using a similar underlying structural entry model. We emphasize heterogeneity in ability while Greenstein and Mazzeo emphasize product variation. Our paper therefore complements theirs in that both emphasize the importance of firm-level heterogeneity in understanding the CLEC market.

Behavioral Game Theory and the CH Model

The first step in building an entry model that links managerial ability with strategic actions is to select an estimable model that fits our real world oligopolistic setting. Camerer's (2003) textbook provides a detailed review of behavioral models of play in simultaneous games, including quantal response equilibrium, level-k thinking, and cognitive hierarchy (CH). We focus on CH for its clarity and parsimony in our context. Specifically, CH includes a single parameter that unambiguously identifies players as being better at playing the game.[4]

Specifically, CH theory posits a hierarchy of rationality. Type 0 players do not consider their competitors; they either pick randomly (as in Camerer, Ho, and Chong 2004) or they act as if the competition is not relevant to their decision (as in Goldfarb and Yang 2009). Type 1

[4] Haile, Hortacsu, and Kosenok (2008) show that quantal response equilibrium is not separately identified from a perfect Bayesian equilibrium with noise and therefore strategic ability is not identified at all. K-step models other than CH allow for players to be too sophisticated in that they may overestimate the ability of their competitors and end up performing worse. The CH model is useful here because it defines sophisticated players as those who *better* conjecture competitor behavior.

players assume all other players are type 0, type 2 players assume all other players are a combination of types 0 and 1, and type k players assume all other players are distributed between types 0 and k-1. A Poisson distribution effectively describes the distribution of types in lab experiments, and the model assumes that a type k player assumes all other players are distributed with a truncated (between type 0 and type k-1) version of the same Poisson distribution. Therefore, for high enough k, type k and type k+1 players will have approximately the same beliefs and these beliefs will match the true frequencies. Camerer, Ho, and Chong (2004) show that CH works well in both entry games and “beauty contest” games.

The most distinctive feature of the CH model lies in the limited rationality of all players, who fail to recognize the existence of other equally if not more strategic players. Beliefs are therefore not mutually consistent. Instead, each player acts if they can perfectly predict their rivals’ actions. The outcome can be short lived because players may revise their beliefs and have an incentive to deviate once they observe others’ actions. The outcome can also be long lasting if changing actions is time-consuming and costly, or noises in the environment delay (or even prevent) players from updating their beliefs. While fully acknowledging several caveats, we argue that our focus on a new industry, where naivety and noise are prevalent, gives us an ideal platform for the application of the CH model.

Related Models

We apply the CH model to an entry game. There is a rich literature on estimation of entry games in economics starting with Bresnahan and Reiss (1990, 1991). They link population thresholds for entry with changes in firms’ competitive conduct by estimating a static entry game from cross-sectional variation in the number of firms and in population. The numerous papers that extend the Bresnahan and Reiss framework to other settings try to better accommodate firm-level heterogeneity into the model. The main challenge in modeling heterogeneous firms' strategic entry in a simultaneous setting is that multiple equilibria almost always arise. Previous researchers have had to forgo firm-level information and only study the numbers of different types of entrants in an equilibrium (Mazzeo 2002), to revise certain features of the game such as information structure (Seim 2006), to estimate the game under different equilibria to check robustness (Jia 2008), or to focus on bounds instead of point identification (Ciliberto and Tamer 2009). Our paper provides a solution to this problem from an alternative angle. By revising the behavioral assumption from complete to limited rationality, we are able to pin down a unique outcome and are therefore able to utilize rich firm-level information in an entry game instead of abstracting the differences away or focusing on just a few categorical variables.

Aradillas-Lopez and Tamer (2008) discuss the identification problem in several simple games with an alternative behavioral assumption based on the concept of rationalizability (e.g. Bernheim 1984).[5] Collard-Wexler (2008) takes their model to data. Their goal is to relax the assumption of Nash Equilibrium behavior but the players in their games are still rational as they play strategies that are consistent with a set of proper beliefs. They do not allow ex-ante heterogeneous players nor estimate the level of rationality; instead, they develop bounds on model parameters as the minimum level of rationality in the market increases. In contrast, our goal is to relax the assumption of rational players. Our model allows us to incorporate heterogeneity in ability across firms/managers, which can impact the quality of the strategic decisions they commit. Furthermore, as we have point identification, we are able to compare the fit of our model against a Bayesian Nash Equilibrium model with fully rational players.

[5] Specifically, Aradillas-Lopez and Tamer model level 0 as the set of all possible actions, level 1 as the set of all possible best responses to level 0, level 2 as the set of all best responses to level 1 (that are also best responses to level 0), etc.

A growing literature in "behavioral industrial organization" has mostly focused on understanding how behavioral biases in consumers affect firm behavior and market outcomes. DellaVigna and Malmendier (2004, 2006) and Oster and Scott Morton (2005) show how firms develop pricing strategies in the presence of non-rational consumers. Hossain and Morgan (2006) and Simonsohn and Ariely (2008) document biases in buyer behavior on eBay. On the seller side, Genesove and Mayer (2001) document loss aversion in the housing market. Hortacsu and Puller (2008) show that older, more experienced firms behave closer to the Nash equilibrium prediction than other firms in electricity auctions.[6] Much of the recent theory literature has focused on how behavioral biases can persist in equilibrium (Esponda 2008; Spiegler 2006; Gabaix and Laibson 2006). Reviews of this literature can be found in sections of Ellison (2006) and DellaVigna (2009).

A small number of other papers have used structural estimation to understand behavioral biases in firms (Brown, Camerer, and Lovallo 2007; Che, Sudhir, and Seetharaman 2007; Lim and Ho 2007), consumers (Conlin, O'Donoghue, and Vogelsang 2007; Laibson, Repetto, and Tobacman 2009), and workers (Paserman 2008). More closely related to the present study, Goldfarb and Yang (2009) apply a similar CH-based model to data on 56k modem adoption by Internet Service Providers. Lacking data on manager and firm characteristics, Goldfarb and Yang emphasize simulation results showing that firms with higher estimated ability were more likely to still be operating 10 years later and that an increase in strategic ability would have slowed the diffusion of 56k modems. Our research builds on this paper by adding manager-specific data, by

[6] Our contribution is distinct from Hortacsu and Puller (2008) in three important ways. First, we focus on manager characteristics rather than firm characteristics. Second, our structure draws from behavioral game theory to provide a plausible theoretical mechanism for the deviations from Nash. Third, our results help understand how Nash equilibrium behavior may change over time.

fully clarifying the identification given this data, by comparing results before and after a shakeout, and by comparing with Seim's (2006) model.

Relating Manager Characteristics to Actions and Performance

By exploring which manager characteristics correlate with more steps of thinking, we address a growing literature on the role of managers in firm performance. Bloom and Van Reenan (2007) examine the correlation between management practices, management characteristics, and productivity. Kaplan, Klebanov, and Sorensen (2008) show correlations between success and specific interpersonal and execution skills. Malmendier and Tate (2005, 2008) relate CEO perceptions of their own ability to underperformance. Bertrand and Schoar (2003) track top managers as they move across firms and show that decisions correlate with manager age and education. Chevalier and Ellison (1999) show that mutual funds managers who attended better undergraduate institutions obtain higher returns even after adjusting for behavior differences and selection biases. Camerer et al (1997) provide some suggestive evidence that more experienced taxi drivers are less susceptible to reference dependence. Finally, Baker, Ruback, and Wurgler (2007) review a large and growing related literature on behavioral corporate finance.

3) Data and Motivating Analysis

3.1) Data Description

We combine information from several sources to create a unique dataset of firms' entry decisions, firm and manager attributes, and location characteristics.

First, we use the 1998 and 2002 CLEC annual reports from the New Paradigm Resources Group, Inc. (NPRG). These reports contain information on the universe of facilities-based CLECs in the United States since the passage of the *Telecommunications Act of 1996*. NPRG provides a detailed profile of every CLEC on its history, management, ownership and organization, and state certification. From the profiles, we know all local voice markets a CLEC served and the exact year of the entry. We define entry as whether the CLEC provided dial-tone service over a landline in the market. We define potential entry as whether the CLEC was licensed to operate in the state (even if the CLEC was not yet operating at any location in the state). We have firm attributes such as the year the company was founded, whether it is public or private, whether it is venture-capital backed, and whether it is a wholly owned subsidiary of a larger communications company (which affects the incentives and influence of managers over company decisions). We also construct two measures of firm survival. The first defines survivors as the set of firms from the 1998 data that are also in the 2002 NPRG data. The second, broader measure defines survivors as the set of firms for which we could not find evidence of exit because of bankruptcy or firm-acknowledged failure.[7] In addition, for a subset of CLECs, we have limited information on revenues (overall and from local phone service) and the number of employees.

Second, using the information on CEO names from the NPRG reports, we conducted a thorough search of several publically archived sources to identify CEO characteristics, including education (highest degree, field of study, and school attended), age, and industry experience. For public companies, this information is typically available in the Form 10-K annual business and financial report. For private companies (and to fill out the remaining gaps for managers of the public companies), we used a variety of public sources including Who's Who directories, news

[7] Specifically, we use three sources for this alternative definition: 1) the NPRG reports mention some reasons for exit (the firms that disappear from the 2002 NPRG report without explanation are not counted as exits under this definition), 2) Crandall (2005) mentions several bankruptcy-related exits, and 3) newspaper archive searches generate more exits due to failure. This definition is broader because it separates survivors from clear failures. Some firms may disappear from the NPRG report (and thus from the CLEC industry) but continue to operate in other industries. Other small CLECs may go out of business without any mention of why in the NPRG report or the press. Therefore, they would disappear from the NPRG report but we would lack evidence of a clear failure.

archives, company websites, and other Internet sources.[8] In the end, we have education information for 90% of the CEOs in our data, age information for 99%, and experience information for 97%.

As discussed in Griliches (1986), there are two standard approaches to missing data in the literature: (1) drop the missing data and (2) impute values using other covariates (based on a linear prediction). In our context, dropping the missing data is not possible because we need to know the full set of CLECs who are potential entrants in a market. Therefore, we impute the missing manager-level data using four firm-level characteristics: firm age, whether the CLEC is a subsidiary of a larger communications company, whether the CLEC is privately owned, and whether the CLEC is venture backed. Our results are robust to including the non-missing manager characteristics in the imputation and to treating the missing values non-parametrically with a "data-missing" dummy.[9]

Lastly, we obtain information on location characteristics from the 2000 US Census, from the 1997 US Economic Census, and from the Federal Communications Commission. The locations in the NPRG reports are best interpreted at the Census "place" level rather than the county or metropolitan statistical area. From the population census we selected the following variables for our analysis: population, household income, racial composition, median age, number foreign born, household size, and poverty rate. From the economic census, we use place-

[8] Both coauthors and an undergraduate research assistant conducted the search. All information found by the research assistant has been confirmed by one of the coauthors. The search algorithm is as follows: 1) if public, search 10-K reports for biographical information (otherwise skip to Step 2), 2) search company websites for biographical information, 3) search *Who's Who* archives, 4) search news archives for mentions of the company and the individual in the same article (allow for alternative names such as Bob for Robert), 5) search Google for mentions of the company and the individual, 6) search news archives and Google for mentions of the individual; then confirm that it is the correct individual by triangulating with other sources on the individual's career path, 7) search public profiles on social networking websites, 8) have a second person visit each source and confirm.

[9] The statistics literature has shown that imputation leads to consistent estimates, even in non-linear models (Allison 2002). In contrast, "data-missing" dummies can lead to biased coefficients (though the signs do not change, at least in linear models). The weakness of imputation is that it overstates the precision of the coefficient estimates by assuming the imputed value is known rather than estimated.

level information on the number of establishments, the number of employees per establishment, and the fraction of firms in manufacturing.[10] We include controls for both business and residences because CLECs catered to both business and residential customers. From the Federal Communications Commission, we use data on the incumbent local exchange carrier (GTE, Regional Bell Operating Company, etc.). In one robustness check, we use information from the FCC on whether there were any competitive access providers in the place prior to 1995 (Federal Communications Commission 1999).

This combination of NPRG data, manager characteristics data, and census data has several appealing features. We have information on all entry by all firms from the effective start of the industry. We can match this to rich data on firm and manager characteristics, including information on manager education and experience, and to measures of the demographic appeal of each market. Finally, a feature of the local telephone industry enables us to identify a set of potential entrants in each market without assuming that all firms can operate everywhere. Specifically, CLECs must first be approved by state regulators before they can operate in a given state. Once approved, the CLEC can operate anywhere it chooses within the state. Therefore, we identify potential entrants as the set of CLECs approved to operate in the state.[11] In the analysis that follows, we cannot separate firm decisions from manager decisions because, in the first year of the industry, firms and managers are observationally equivalent. Therefore the unit of observation is the firm-place (or equivalently, the manager-place).

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[10] This information is only available for the following 2-digit NAICS industries: manufacturing (31-33), wholesale trade (42), retail trade (44-45), real estate and rental housing (53), management and remediation (56), educational services (61), health care (62), arts, entertainment and recreation (71), accommodation and food (72) and other services (81). Therefore the variables are compiled based on these industries only. This information was missing for 6 of the places in our data. For these places, we used county-level data and used the population-proportionate values for the business statistics.

[11] It is important to note that while regulatory approval is necessary for entry, it is not sufficient. Among the 96 CLECs approved to operate in 1998, just 56 actually entered at least one market in that year and only 79 had entered by 2002. Based on the NPRG reports, we believe that our definition of potential entrants is both simple and realistic. We check the robustness of our definition by excluding CLECs that had not entered anywhere by 2002.

Tables 1a, 1b, and 1c provide descriptive statistics. Table 1a shows that these firms are generally privately owned (64.5% in 1998) and have a high variance in age (the standard deviation is over twice the mean of 7.9 years in 1998). The managers average 18 years experience in the industry and are highly educated. Of the firms operating in 1998, 58% of managers have a graduate degree and 78% have at least one degree in economics or business. The table also shows the high turnover rate in the industry. Nearly 60% of the firms that operated in 1998 were no longer operating as CLECs in 2002. Table 1b describes the 234 mid-size cities that we use in our analysis. The average market has 2 CLECs operating out of 25 potential entrants (who are licensed to operate in the state). The number of entrants ranges from 0 to 18 while the number of potential entrants ranges from 8 to 35. Table 1c summarizes the data at the firm-market level.

3.2 Motivating Analysis

In this section, we present descriptive evidence of a systematic relationship between manager characteristics and firm actions. Consistent with Figure 1, we show that firms with older and appropriately educated managers tend to enter markets with fewer competitors. In particular, we estimate the following Logit regression for firm j in market m:

$$Entry_{jm} = \alpha_0 + \alpha_1 (\#competitors)_m + Z_j \alpha_2 + (\#competitors)_m Z_j \alpha_3 + X_m \alpha_4 + \varepsilon_{jm} \tag{1}$$

where $Entry_{jm}$ is a binary variable for the entry decisions of firm j in market m; Z_j are manager and firm characteristics including age, experience, and education (field of specialization, undergraduate school quality, and whether the manager has a graduate degree) as well as firm age, whether the firm is a subsidiary of a larger communications company, whether the firm is venture-backed, and whether the firm is privately held; X_m are market characteristics including population, household income, racial composition, median age, percentage foreign born, household size, poverty rate, number of business establishments, average number of employees per establishment, and the percentage of establishments that are in manufacturing; and ε_{jm} is the error term. Of interest in this regression are the signs of the interaction terms between the number of competitors and manager characteristics (α_3), which measure whether manager background mediates the relationship between competition and entry. To address concerns expressed in Ai and Norton (2003), we confirmed that marginal effects at mean values yield the same sign as the interaction terms.

The number of competitors in the above regression is potentially an endogenous variable, which may be correlated with unobserved market-level heterogeneity. In this descriptive analysis, we rely on demographic controls to address this issue and emphasize that the purpose of this subsection is to document an intriguing relationship between manager characteristics and firm entry decisions. In the main analysis that follows, the structure of the model uses the characteristics of the managers of other potential entrants as implicit instruments for the number of competitors.

We focus on manager age and whether the manager's undergraduate institution was ranked in the US News list of the top 25 universities because these proved to be the most robust results across specifications both in the descriptive and in the structural analysis. The results on experience and field of study appear to show a similar relationship between managerial ability and firm actions although in many specifications the results lose significance.

Table 2 shows the results. The negative coefficients in the first two rows show that older managers and managers undergraduate degrees from top schools are more likely to enter markets with fewer competitors. Columns 1 through 4 use variants of the specification in Equation (1).

Column 1 includes only demographic controls. Column 2 adds controls for firm characteristics and interacts them with the number of competitors. Column 3 adds controls for other manager characteristics and interacts them with the number of competitors. In terms of the covariates included, this column is closest to a reduced-form version of our structural model. The positive coefficient in Row 26 suggests that inexperienced managers are more likely to enter markets with more competitors. The negative coefficient in Row 28 suggests that managers with degrees in economics or business are more likely to enter markets with fewer competitors. Column 4 repeats Column 3 but with a linear measure of experience. Because the discrete measure of experience in Column 3 fits the data much better, in our structural analysis we use the discrete measure. Column 5 includes interaction terms between manager characteristics and the demographic controls related to demand potential.

Overall we see this table as suggestive of an intriguing, and perhaps non-standard, relationship between manager characteristics and firm entry decisions. Older managers and managers who attended a higher quality school appear to be better at anticipating competitor decisions that occur at roughly the same time. Because the market-level demographics control for the overall appeal of the market, this is not simply a matter of older, better educated managers entering markets with lower populations. It is that they somehow enter markets that others choose not to enter. Next, we develop a model that puts a useful structure on this relationship. The structure provides insight into manager decisions in a newly forming industry.

4 Model and Identification

4.1) Model

In this section, we describe how we model heterogeneity in managerial ability in an oligopolistic entry game.[12] The model we use assumes simultaneous decision-making. While no real world entry decisions are truly simultaneous, we believe simultaneity is a reasonable assumption in the CLEC industry in 1998. The industry was new and implementation took time. While a handful of CLECs operated (as competitive access providers, or CAPs) in large metropolitan areas prior to the Act, the NPRG reports suggest most CLECs became operational in 1997 and entry into midsized markets took off in 1998. In addition, while companies did announce "planned" market entry, there appears to be little correlation between these plans and actual entry decisions in mid-sized markets.[13] In the end, the simultaneity assumption, though often just a convenient way to limit manager information sets about competitor actions in the literature, works well in our setting where the opening of a new industry meant high volatility and uncertainty.

Our empirical model contains two significant deviations from the one used in laboratory experiments. First, we incorporate market- and firm-level covariates in order to allow entry incentives to vary across markets and managerial ability to vary across firms. In the laboratory, the controlled environment means this is not necessary. Second, type 0 players in our model choose whether to enter based on the expected profitability of the market if they face no competitors rather than choosing randomly as in Camerer, Ho, and Chong (2004). This is a more

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[12] This section builds on the model in Goldfarb and Yang (2009).

[13] Many planned entries never happened, and many observed entries were never listed as "planned." One possible explanation for this is that "planned" entries were cheap talk meant to appease regulators. Our data also suggest there is considerable time spent building a facilities-based network. For example, Teligent's deployments in 1998-99 took between six and eighteen months, depending on the market.

reasonable assumption in a real world setting because it is unlikely firms are unaware of public information or deliberately ignore the fact that larger markets have more potential customers.

More formally, let j $(j=1,2...,J)$ index the firm (or, equivalently in our data, the manager of the firm), and m $(m=1,2...,M)$ index market. At a given time period, J_m potential entrants are simultaneously deciding whether to enter market m. Market-level demand and cost factors are public information except for a firm- and market-specific stochastic term. All firms make decisions based on these market-level factors and the expected competition from other firms. However, firms have heterogeneous ability in inferring the potential level of competition. In each market, each firm draws its type, k $(k=0,1,2...,K)$, from a Poisson distribution with a firm-specific parameter τ_j. In notation, we have: $k \sim Poisson(\tau_j)$. This τ_j $(\tau_j > 0)$ is a deterministic function of firm and manager characteristics.[14] Parametrically, $\tau_j = \exp(\gamma_0 + Z_j\gamma)$, where Z_j is a vector of all the covariates that affect the strategic ability of firm j.[15] Each τ_j is public information.

Firm j knows its own type but does not observe its competitors' specific types. Therefore, in each market, each firm makes an inference about its competitors' types based on its own type and public information on the firm and manager characteristics of its competitors. A type k firm believes all its competitors have lower types up to $k-1$. Specifically, it believes that a potential competitor i $(i \neq j)$ has a type drawn from a Poisson distribution with parameter τ_i, truncated at $k-1$. In notation, we express this truncated Poisson distribution with an extra

[14] We do not include an error term in τ_j for two reasons. First, there is already randomness in generating types through the Poisson mapping from τ_j to any specific type *k*. Second, the variance of the error in the τ_j function would be a loose parameter that could not be identified without further strong parametric assumptions.

[15] We use exponential functional form to ensure τ_j is non-negative, as required by the Poisson distribution.

parameter: $Poisson(\tau_i, k-1)$. If the potential competitor has a high τ_i, firm j will perceive i as more likely to be a higher type. However, firm j's guesses about this competitor are effectively truncated by how strategic she is herself. If she is a higher type, she is subject to less truncation in her conjecture and thus able to guess the competitors' types more accurately. As described here, every player in this game has limited rationality as each systematically underestimates the types of its competitors, though the extent of this underestimation varies.

A potential entrant decides whether the expected discounted value of the future profit stream is sufficiently high to support its entry. Upon actual entry, firm j's payoff in market m is given by the following formulation:

$$\Pi_{jm} = \beta_0 + X_m\beta + \psi(\#competitors)_m + \xi_m + \varepsilon_{jm} \tag{2}$$

We adopt the above reduced-form profit function for its tractability. Equation (2) states that the firm's actual payoff of entry depends on a vector of time-invariant market attributes X_m, the competition it will encounter upon entry, a market-specific random term ξ_m, and an idiosyncratic error term ε_{jm} with a standard normal distribution reflecting unobserved firm- and market-specific heterogeneity in expected profits. In the above formulation, X_m contains market-level observables that might affect the profitability of market m. Market size, as measured by population, is a key element as in Bresnahan and Reiss (1990, 1991) and the literature that follows. In the local telephone market, other plausible elements of X_m include local demographic variables such as age profiles and income levels, local business activity variables such as the total number of business establishments, and whether the incumbent local telephone company is GTE, a "Baby Bell," or another company. Still, it is likely that these controls do not capture all factors which affect profitability of market m that the firms observe before they make entry decisions. Therefore, we introduce a market-level random term ξ_m to capture unobservable exogenous heterogeneity across markets. We assume $\xi_m \sim N(0, \sigma_\xi)$, that is, ξ_m has a normal distribution with standard deviation σ_ξ. The magnitude of σ_ξ informs us about the degree of correlation of entry decisions by different firms into the same market. We assume that ξ_m is public information observed by all firms (but not by the econometricians) while ε_{jm} is private information of firm j.

In our model, each potential entrant acts upon her own type-variant expected discounted value of future profits, $E(\Pi_{jm} \mid k)$ instead of the actual payoff.[16] Based on the type of the manager of the firm in the market, equation (2) becomes:

$$\begin{aligned} E(\Pi_{jm} \mid k) &= \beta_0 + X_m\beta + \psi E\left[(\#competitors)_m \mid X_m, \tau, k\right] + \xi_m + \varepsilon_{jm} \\ &= E(\overline{\Pi}_{jm} \mid k) + \varepsilon_{jm} \end{aligned} \quad (3)$$

The entry decision of firm j is a dichotomous variable $D_{jm} \in \{0,1\}$ where $D_{jm} = 1$ if firm j enters market m and $D_{jm} = 0$ otherwise. Firm j will enter the local market if the expected discounted value of future profits is positive; that is, $D_{jm} = 1$ if $E(\Pi_{jm} \mid k) \geq 0$, and $D_{jm} = 0$ otherwise.

The novelty of this framework is the variation in firms' perceptions about the expected level of competition in each market; that is, $E\left[(\#competitors)_m \mid X_m, \tau, k\right]$ in Equation 2. The expectation is conditioned on market attributes X_m, all the potential entrants' strategic ability parameter τ, and each firm's own type k. A type 0 firm, which does not take competitor entry into consideration, has an expected discounted value of future profits of:

[16] Note that a potential entrant's expected profit is conditional on her own type k, market demographics X_m, and the firm/manager characteristics of all other potential entrants in the same market. We use $E(\Pi_{jm} \mid k)$ to simplify notation.

$$E\left(\Pi_{jm} \mid 0\right)=\beta_0+X_m\beta+\xi_m+\varepsilon_{jm} \tag{4}$$

A type 1 firm, which perceives all its potential competitors as type 0 players, has an expected discounted value of future profits of:

$$E\left(\Pi_{jm} \mid 1\right)=\beta_0+X_m\beta+\psi E\left[\sum_{i=1,\ldots,J_m}^{i\neq j} D_{im} \mid X_m, Poisson\left(\tau_i,0\right),1\right]+\xi_m+\varepsilon_{jm} \tag{5}$$

where $Poisson(\tau_i,0)$ means that firm j, as a type 1 player, perceives any of its potential competitor i's type to be drawn from a Poisson distribution with parameter τ_i and truncated at 0. The truncation means that the type 1 player assigns 100% probability to its competitor's likelihood of being a type 0. For a type 1, the assumed distribution is therefore not relevant. The type 1 then uses the profit function specified in Equation 3 to figure out expected number of entrants. We can iterate using the same logic and write down any type's expected discounted value of future profits. For a firm of type $k\geq 2$, its perceived distribution of any competitor i's type is drawn from $Poisson(\tau_i,k-1)$. As k increases, the discrepancy between $Poisson(\tau_i,k-1)$ and $Poisson(\tau_i,k)$ gradually disappears and the truncated Poisson gradually approaches the real Poisson distribution.[17] That is, a very high type player is able to make decisions based on nearly correct beliefs on its rivals' expected behavior. With more correct beliefs, higher types are less likely to make decisions which will generate ex-post regret after they observe the actual entry decisions of their competitors. As entering saturated markets and not entering unsaturated markets both cause ex-post regret, a higher type means a higher ability to avoid both types of entry-related errors.

[17] In estimation, we need to pick a maximum number of types because it is impossible to derive entry likelihood for an infinite number of types. We do this by increasing the number of types and repeating the estimation until the results no longer change. In our analysis, the results are stable at eight or more types.

A crucial feature of the above iterative process is that each firm acts if she can predict her competitors' entry probabilities (the only exception is the naïve type 0, who completely ignores competitors). A type 1 player perceives every other player in the game to be type 0, and acts upon this belief. A type 2 player perceives every other player to be either type 0 or 1 according to a truncated Poisson distribution with a known parameter, and she then calculates the entry probabilities of any competitor. A player of any type in this game, due to her own limited rationality, best responds to the perceived actions of her competitors, even though the perception can be incorrect. As a result, the entry game we have specified generates a unique outcome by eliminating the "double-guessing" nature of a game in which players are equally rational. In other words, there will not be multiple equilibria in our model as each player in this game only has one action to follow based on its (incorrect) beliefs.

The estimated parameters are $\theta = \left[\beta_0, \beta, \psi, \gamma_0, \gamma, \sigma_\xi\right]$. Of these parameters, β measures how a firm's expectation about a market's profitability is affected by X_m, ψ measures how the same expectation is affected by the perceived competition, γ measures how firm- and manager-specific characteristics shift a firm's strategic ability, and σ_ξ measures the importance of unobserved market-level heterogeneity. As econometricians, we identify the degree to which manager and firm characteristics correlate with the latent ability distribution parameter, τ_j, rather than the exact number of steps of consideration the firms undergo in each market. The number of steps of consideration is the firm's private information, and therefore both the firm's rivals and we the econometricians can only assess the probability of each possible type given our knowledge or estimate of τ_j, which is a function of firm- and manager-specific characteristics. Therefore, to estimate θ, we need to evaluate each firm's entry probabilities by conditioning on all possible types in each market and integrate these probabilities over the distribution of types to predict the entry probability of this firm unconditional on types. We match the entry probabilities of all firms to the data using a standard method of maximum simulated likelihood procedure. Specifically, we maximize the simulated log likelihood:

$$\ln L_{simulated} = \sum_{m=1,\ldots,M} \ln\left\{\frac{1}{R}\sum_{r=1}^{R}\left[\prod_{j=1}^{J_m}\left(prob\left(D_{jm}^{r}=1\right)^{D_{jm}} prob\left(D_{jm}^{r}=0\right)^{1-D_{jm}}\right)\right]\right\} \qquad (6)$$

In (6), R denotes the number of simulation draws—20—we use for the market-level random term ξ_m and D_{jm}^{r} denotes the simulated entry decision under an individual simulation draw r. The full likelihood function is provided in the appendix.

4.2) Identification of Model Parameters

Assuming our model is the true model underlying the data generating process, next we discuss the identification of the parameters $[\beta,\psi,\gamma_0,\gamma]$ in the model. Our model examines the association between firms' entry behavior and market and firm (manager) characteristics. In the data, we observe variation in (a) the probability of entry by the same firm across different markets and (b) the probability of entry by different firms into the same markets. To account for these variations, we observe the following explanatory variables: (c) market characteristics (population demographics and business presence), (d) the number of potential entrants in each market, and (e) firm and manager characteristics. The identification of β is straightforward—the association between market characteristics as in (c) and entry probability variation across markets as in (a) allows us to identify the coefficients for market demographics (β). Here we focus on the separate identification between the competition effect ψ and the level of manager ability τ (determined by γ_0 if there are no covariates for firm and manager characteristics).

As we have two structural parameters to be separately identified, we need to develop at least two sets of restrictions from data to uniquely determine them. The first restriction is from the association between the residual entry probability across markets—what is left to be explained in (a) after β is identified—and the variation in the number of potential entrants as in (d). Clearly the competition effect ψ helps to explain this association because the number of potential entrants enters the profit function only as a determinant of the number of actual entrants. For example, if entry probability drops going from a market with a small number of potential entrants to an otherwise identical market with a large number of potential entrants, we know that the impact of competition (ψ) is negative and the magnitude of the drop in entry probability gives us information about the magnitude of this negative competition effect. However, this magnitude is confounded with the strategic level of players in the market. For example, the same entry probability can be attributed to a combination of a small competition effect and a high level of strategic ability, or to a large competition effect and a low level of strategic ability.

The second restriction from data is the *variance* across firms in propensity to enter the same market (b). From our model we know that, conditional on market-level variables and the competition effect ψ, a type 0 has a very high entry probability, a type 1 has a very low entry probability, and a type $k\left(k \geq 2\right)$ is in the middle with some oscillation across types. This means that conditional on market-level variables and the competition effect ψ, the average entry probability can be in the middle because the market is evenly distributed between type 0 and type 1 or because the market is populated mostly with higher types. However, if there is a large proportion of type 0's and 1's, which correspond to low level of τ, we will see large variation in entry probability across firms. In contrast, when the market is comprised mostly of higher types, we will see small variation in entry probabilities across firms. With the two restrictions, we should be able to separate ψ from τ in general. That is, we use both the first (average entry probability of the same firm entering different markets) and the second moment (variance in probability of different firms to enter the same markets) to identify τ and ψ through deviation from what would appear to be average behavior given β.[18]

Finally, the matching between firm or manager characteristics as in (e) and variation in entry probability across firms as in (b) helps identify the coefficients γ for the covariates in the τ function. For example, if firms with more experienced managers are systematically less likely to enter markets with a large number of potential competitors, our model will generate higher τ and therefore an increased likelihood of high types for managers with more experience. The firm or manager characteristics serve the additional role of implicitly instrumenting for the endogenous expected number of competitors. As discussed in the earlier descriptive analysis, the expected number of competitors is endogenous: unobserved market level heterogeneity may drive the entry decisions of *all* potential entrants and in turn drive the expectation on potential competition. As with standard instrumenting techniques, we need to find variables that affect the expected number of competitors that potential entrant j faces but do not otherwise affect the entry decisions of potential entrant j. The characteristics of the other potential entrants in the same markets serve this role.[19] They only affect the formation of the expectation of the number of competitors, and they are determined independently from the realization of the market level unobserved heterogeneity. In our iterated steps to construct the likelihood of entry for each firm

[18] As the variance in probability of different firms to enter the same markets is not necessarily monotonically decreasing for the entire range of τ (for example, the variance converge to zero as τ goes to zero), we may need to use higher moments (more than two restrictions) to separate τ and ψ. Our likelihood estimator enables us to use information provided by all moments in firms' entry probabilities.
[19] In fact, for exact identification we only need one such characteristic.

into each market, we use these excluded exogenous variables to predict the expected number of competitors; that is, they function as implicit instruments.

4.3) Validity of underlying modeling assumptions

Now we turn to the validity of the underlying modeling assumptions, which state that a manager's ability (primarily measured by education quality and age) only affects expected profitability of entry through the ability to correctly conjecture the number of competitors. For identification of the role of managerial ability we need this assumption to hold for at least a subset of manager characteristics. This means that we need a subset of manager characteristics to play no role in other drivers of success such as assessing market potential, reducing costs, pricing, exercising quality control, etc. Otherwise managers will choose markets based on their own and their competitors' ability but not for the reason assumed in our model. For example, rather than the ability to correctly conjecture competitor behavior, better-managed firms may be in less competitive markets because other firms choose not to compete with them.

Clearly, the exclusion assumption we have made above is a strong assumption. We will not argue for its universal validity. Instead, we will provide evidence suggesting that this assumption is reasonable in our particular setting.

First, to alleviate the concern that manager characteristics may drive post-entry decision quality, we show that our focal subset of manager characteristics is uncorrelated with survival (a measure of realized profits) conditional on entry. We establish this fact in order to demonstrate that some manager characteristics appear to affect expected profits through entry decisions, not through post-entry decisions. To express this idea more formally, following the notation we have developed above we can write the identification assumption as:

$$E\left(\Pi_{jm} \mid D_{jm}=1, X_m, (\#\,competitors)_{\mathrm{m}}\right) = E\left[\Pi_{jm} \mid D_{jm}=1, X_m, (\#\,competitors)_{\mathrm{m}}, subset\left(Z_j\right)\right] \qquad (7)$$

which states that conditional on entry ($D_{jm}=1$), market characteristics, and the number of competitors of the market, a subset of manager characteristics Z_j do not affect expected realized profits Π_{jm}. As we do not directly observe realized profits at the firm-market level but observe a function of realized profits at the firm level, such as survival, the above assumption leads to:

$$E\left(f\left(\Pi_{jm}\right) \mid D_{jm}=1, X_m, \left(\#\,competitors\right)_{\mathrm{m}}\right) = E\left[f\left(\Pi_{jm}\right) \mid D_{jm}=1, X_m, \left(\#\,competitors\right)_{\mathrm{m}}, subset\left(Z_j\right)\right] \quad (8)$$

and this equation serves as the basis of the regression we run for identification:

$$f\left(\Pi_{jm}\right) = \delta_0 + Z_j\delta_1 + X_m\delta_2 + \delta_3\left(\#\,competitors\right)_{\mathrm{m}} + \varepsilon_{jm} \qquad for \quad D_{jm}=1 \qquad (9)$$

Our identifying assumption implies the null hypothesis: $H_0: \delta_1 = 0$.

Table 3 presents results from the above (Logit) regressions, where we use survival as our proxy for realized profits. The first two rows of Columns 1 and 2 show that our focal manager characteristics (age and whether the manager attended a US News top 25 undergraduate institution) are not significantly related to survival conditional on entry. In contrast, they are significantly related to survival (and much larger in magnitude) in the unconditional regressions in Columns 3 and 4. Despite several weaknesses,[20] the results are consistent with our identifying assumption that the focal manager characteristics relate to profits primarily through entry.

Second, to address the concern that manager characteristics are related to an ability to estimate market potential prior to entry, we show that the number of competitors mediates the correlation between manager characteristics and entry decisions more strongly than demographic

[20] Specifically, this test is weak for three reasons. First, our proxy for realized profits varies at the firm level rather than the firm-market level. Second, while not necessary for identification, the results for the non-focal managerial characteristics are less clear. Specifically, the magnitudes of the coefficients are higher in the conditional on entry case for experience and education field (though not for graduate degree). This limits our interpretation of the non-focal characteristics in the structural model. Third, the direction of the relationship with survival is sometimes surprising. For example, age, a degree in economics or business, and a graduate degree are negatively correlated with survival in the unconditional regressions. Still, on balance we believe this analysis supports our identifying assumption that entry plays a particularly important role in mediating the role of manager characteristics on profits, particularly for manager age and undergraduate institution quality.

characteristics such as population. Table 2—described earlier to show that better educated, older managers enter markets with fewer competitors—shows that there is no clear relationship between manager characteristics, demographic characteristics, and entry. While the interaction of the number of competitors with our manager ability covariates displays a consistent negative relationship with entry, we find no consistent relationship with demographic characteristics. For example, Column 5 shows mostly insignificant coefficients on the interactions between demographics and our focal covariates for ability. We see no systematic pattern suggesting that older and better educated managers make different estimates of market potential (or that they pick markets with different observable characteristics) than other managers. While this is not a definitive test, it is highly suggestive that the relationship between manager characteristics and the number of competitors is particularly important in our setting.

In this section we have provided evidence to suggest: 1) entry decisions drive the correlation between success and the focal manager characteristics; 2) it is the number of competitors (instead of, for example, managers' ability to measure market potential) that drives the correlation between entry decisions and manager characteristics. As such, we argue that our identification strategy, which relies on correlation between manager characteristics and strategic entry considerations, is reasonable in our context.

5) Results

We first present the coefficient estimates for 1998. As discussed above, this was effectively the first year of entry in these mid-sized markets. Therefore, the entry decisions in this period are more likely to be truly simultaneous. After discussing coefficient estimates and their robustness, we demonstrate a positive correlation between the estimates of strategic ability and two measures of firm performance: survival and revenue. We then show that the measured level of strategic thinking increased from 1998 to 2002. We conclude this section by comparing the fit of our model with Seim's (2006) Nash equilibrium model. While our model fits the 1998 data much better than Seim's model, with the 2002 data the improvement in fit of our model relative to Seim's is much lower. We interpret this to suggest that the behavioral assumptions are most relevant in the early years of the industry's life cycle.

5.1) What Drives Strategic Ability?

In this sub-section, we examine whether the standard information on a manager's biography relates to strategic ability. Table 4 Column 1 shows the main estimates. The top part of the table shows the coefficients for the strategic ability function and the bottom part of the table shows the coefficients for market attributes used in estimating the latent profitability of entry. Before turning to our analysis of firm- and manager-level characteristics, we note the strong negative relationship between the expected number of competitors and the level of entry (Row 13). This is the most statistically significant result in almost all specifications and shows that firms appear, on average, to avoid direct competition. Therefore, it is empirically relevant to examine how variation in strategic ability leads to variation in the avoidance of competition.

Rows 1 to 7 show the coefficients for manager-level characteristics in driving measured ability, and Rows 8 to 11 show coefficients for firm-level characteristics. In discussing the results, we focus on three areas: experience, education, and ownership structure. The logged specification means that coefficients in Rows 1 to 11 can be interpreted as the percentage change in τ responding to a change in the covariate.

Age/Experience: Experience is widely viewed as an asset for managers. It is emphasized in manager bios and on company annual reports. Laboratory research has shown experience is positively correlated with ability in beauty contest games (Slonim 2005), and other research has documented a relationship between experience (measured at the firm or manager level) and behavior. Our results support the idea that ability is positively correlated with age and perhaps firm experience. Older managers have higher values of τ (Row 1). This effect is large: one extra year is associated with an 8.5% increase in τ. We also find that older firms have higher values of τ (Row 8). We find little systematic relationship between measured ability and experience measured by years in the telecommunications industry. Controlling for age, inexperienced managers (those with less than 10 years experience) have no significant difference in measured ability from other managers, though the coefficient is negative (Row 2). Oddly, too much experience appears to be bad: managers with over 20 years experience have a lower level of τ (Row 3). We speculate that this might be because these managers had their formative years in the telecommunications industry before the breakup of AT&T and they therefore might view competition differently.

Education: We examine three different aspects of education: quality (Row 4), field (Rows 5 and 6), and level (Row 7). Whether education provides value or merely functions as a signal of ability, we would expect it to correlate with the ability of managers. Managers with a degree from a top-level undergraduate institution (US News top 25) have 5.7% higher levels of τ. Managers with a degree in economics or business also appear to have higher levels of τ, though this result is of marginal statistical significance in many specifications. Still, in all specifications, managers with a degree in economics or business have a significantly higher level of τ than managers with a degree in engineering or science. Whether managers have a graduate degree, however, is not systematically correlated with τ.

Ownership structure: Ownership structure may be systematically related to manager ability because of incentives and experience. We find that CLECs that were subsidiaries of larger telecommunications companies have lower measured ability (Row 9). We see two possible explanations for this: 1) these managers had fewer incentives to be careful in entry decisions because they would be rewarded based on how fast their units grew and their loss could be covered by the mother company, or 2) these managers were chosen to run a subsidiary business because they were either less skilled or less experienced than the others. We believe the former is more likely because the managers of subsidiaries were older and had more years experience than the other CLEC managers in our sample. We find no consistent relationship between measured ability and either private ownership (Row 10) or venture-capital backing (Row 11).

The remainder of Table 4 shows robustness to a number of alternative specifications. Column 2 uses an alternative functional form for τ : $\tau_j = K\Phi(\gamma_0 + Z_j\gamma)$, where $\Phi(.)$ is the density function of the standard normal distribution and K is the maximum number of types we allow for estimation. Column 3 defines potential entrants only as those 79 firms that did eventually enter the CLEC market rather than all firms licensed to do so. And Column 4 excludes the few markets that had at least one competitive access provider with rights to a local telephone number in the fourth quarter of 1994 (though many were not yet operating). In the Appendix, we show robustness to alternative covariates (including just the focal managerial characteristics) and to an alternative treatment of the missing data. The result on manager age is robust to all specifications. The result on whether the manager attended a top 25 undergraduate institution is also generally robust, though it loses significance in some specifications. The significant difference between an economics or business degree and an engineering or science degree is also robust across specifications.

5.2) Do More Strategic Firms Do Better?

Next, we examine whether the CLECs that we estimate to be more sophisticated were in fact more successful. Given that such a large percentage of firms failed, especially after telecommunications stocks crashed in 2001, we use survival to 2002 as our primary measure of success. We also show results using 2002 revenue as another measure of success.[21]

Table 5 shows the results. The core independent variable in these regressions is the predicted value of τ for each firm, based on the coefficients in Table 4 Column 1. We find that the predicted τ is positively correlated with four different definitions of success: 1) survival as defined by appearing in the 2002 NPRG reports, 2) survival as defined by not having an accessible public record of exit through failure, 3) revenue (conditional on survival), and 4) local phone service revenue (conditional on survival).

Because we predict the value of τ from a simple log linear function of firm and manager characteristics, it is important to be cautious in this interpretation. The results will be a consequence of spurious correlation to the extent that these characteristics drive survival for reasons other than strategic ability. Consistent with the prior literature (e.g., Dunne, Roberts, and Samuelson 1988), we especially suspect that firm age and size have effects on firm survival, independent of τ. Therefore, we include these as controls. The results are robust. While certainly not conclusive, we view these results as providing some external validity for our model.

5.3) Measured Strategic Ability in 1998 and 2002

The first two columns of Table 6 compare 1998 and 2002. In the 1998 data, the average value of τ is 3.13 (Row 28). This means that 4% of firms are type 0, 14% are type 1, 22% are type 2, 22% are type 3, 17% are type 4, and 21% are type 5 or higher. The average value is at the

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[21] Ideally, we would have a measure of long term profits. Unfortunately, we do not have profit data and therefore focus on survival and revenue as crude but distinct measures of success.

high end of the range found in Camerer, Ho, and Chong (2004), although it is well below their maximum of 4.9. We view this as supportive of the CH model. We expect the value of τ to be relatively high because this is a more important decision than those faced by laboratory subjects.

Using the 2002 data, τ increases to 4.65. The measure of ability requires a different interpretation in this year because firms could observe what competitors did in the prior periods. Therefore, a simultaneous entry game is less appropriate in this setting. We interpret the increase in measured ability after the 2001 shakeout as supporting evidence for an evolution towards the steady equilibrium outcome assumed in much of the existing simultaneous entry literature (e.g., Greenstein and Mazzeo 2006; Seim 2006).

Although the industry as a whole increased in sophistication over time, the minimum value in the 2002 data suggests that some naïvety persisted. Given that this is an industry with a high turnover rate and that we already showed new firms to be less likely to act strategically, this is perhaps unsurprising. Some questions, however, follow: Do the smart get smarter, while the less strategic firms exit? Or does the entire industry learn over time? And do firms learn from past successes and failures? The dynamic implications of these questions, although beyond the scope of this project, warrant future research.

5.4) Comparison to a Bayesian Nash equilibrium entry model

The CH model relaxes the assumption of mutually consistent beliefs that holds in Bayesian Nash equilibrium. In this section, we compare the fit of our model with a commonly used Bayesian Nash equilibrium model with fully rational players: Seim (2006). In Seim (2006), privately-informed potential entrants are uncertain about the exact actions of their competitors and they form fully rational expectation about these actions. For example, managers' strategic ability and entry cost can be part of this private information. In our model, potential entrants are similarly privately informed and therefore need to form expectations about their competitors' behavior. However we take firm/manager characteristics, and the average ability level associated with these characteristics, out of the private information set and impose the CH structure on how firms form expectations using these characteristics.

The goal of this exercise is to compare the fit generated by the different rationality assumptions. To this end, we estimate a simplified version of Seim's model in which potential entrants only decide which market to enter and hence location differentiation inside a market does not play a role.[22] Seim's model does not incorporate firm/manager-specific exogenous covariates because her nested fixed point algorithm uses a symmetric assumption that every firm has the same equilibrium conjecture of its competitor's location choices.[23] In our specification of her model, we adopt the same symmetric assumption and only use market-level covariates to explain firms' entry decisions. In Table 6 Columns 3 and 4, we present the coefficient results from our estimation of this simplified version of Seim's model.

The estimates suggest few substantive differences in the role of market-level covariates on entry across the two models. One difference is the magnitude of the coefficient on the expected number of competitors. (The difference remains if we consider the marginal impact on entry probability.) The cognitive hierarchy model estimates a more negative impact of competition on entry than the Bayesian Nash model. This makes sense in light of the

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[22] In our estimation, we followed Seim (2006) step by step except for two deviations: 1) a potential entrant only needs to decide whether to enter a market; there is no location choice inside a market and therefore all rivals inside a market have the same competitive effects on a potential entrant's expected profits. 2) in our maximum simulated likelihood estimation, we do not need to solve the market-level random effects by equating actual and predicted number of entrants to alleviate the computational burden because without the location choice our simplified version is highly tractable with little computational burden.

[23] In principle, it is possible to add firm-level covariates into Seim's framework (e.g. Augereau, Greenstein, and Rysman 2006) but this adds two challenges. First, the fixed point mapping with asymmetric firms gives rise to the possibility of multiple equilibria and therefore requires additional structure to allow selection of just one. Second, the computational burden rises substantially (much more than in Augereau, Greenstein, and Rysman) because each firm makes many market-level entry decisions. For simplicity of comparison, we therefore focus on the symmetric context and especially emphasize the comparison across years.

assumptions of the model. Low type firms may enter markets regardless of actual competitor decisions. The degree to which firms avoid the competition therefore depends primarily on the decisions of high type firms. In contrast, the decisions of low and high type firms are mixed together in Seim's model, leading to a lower estimated impact of competitor entry.

Table 7 compares the fit of our model to Seim's both before and after the shakeout. It presents three different measures of fit. The first two rows show the R^2 of a regression of actual entry on predicted entry (predicted from covariate estimates). The next two rows show the Bayesian Information Criterion.[24] The last two rows show the mean squared error. To compare fit, we compare the differences across models within a year.

In all cases, our model performs better than the Bayesian Nash equilibrium model, though we acknowledge that our model's fit benefits from incorporating firm/manager-covariates. Interestingly, the difference in performance varies across years. In the estimates based on 1998 data, our model gives a much higher R^2 than Seim's in the regression of actual entry on predicted entry (0.211 compared to 0.149). In contrast, our model only does a little better than Seim's with the 2002 data (0.169 compared to 0.148). Similarly, the improvement in fit in the Bayesian Information Criterion of using our model is 152 in the 1998 data and just 52 in the 2002 data. Finally, our model's mean squared error is 0.4 lower than Seim's in the 1998 data but just 0.2 lower in the 2002 data.

Therefore, relative to Seim's Bayesian Nash equilibrium entry model, our "behavioral" model does a much better job fitting the data in 1998 than in 2002. We interpret the 1998 result as providing further validity for the assumptions in our model in the first year of the CLEC industry. However, consistent with the sharp rise in estimated ability described above in section

[24] The Bayesian Information Criterion is a commonly used measure of fit. It is equal to $-2lnL+kln(n)$, where L is the likelihood, k is the number of covariates, and n is the number of observations

5.3, the relatively strong performance of Seim's model in 2002 suggests that, after the shakeout, little is lost in applying a standard equilibrium entry model with fully rational players to the data.[25]

6) Conclusions

Overall, our approach provides insight into the incidence of strategic ability in a new market: Local telephone competition following the 1996 Act. We show that firm behavior is related to manager and firm characteristics in a systematic way. Generally, older firms with older better-educated managers made decisions that suggest they were better able to correctly conjecture competitive behavior. In order to better understand this relationship, we impose a structural model of strategic ability based on the Cognitive Hierarchy model.

Several aspects of our results suggest considerable validity for our model in this setting. First, the coefficient estimates are suggestive that the strategic ability parameter, τ, is correlated with education and experience. Managers who attended better undergraduate institutions are estimated to be more sophisticated. Managers with more experience (as measured by age) are estimated to be more sophisticated. Second, our strategic ability parameter correlates with out-of-sample success: Those firms estimated to be more strategic in 1998 were more likely to survive and have high revenues. Third, our estimate of τ increases following the shakeout. This suggests that the industry became more sophisticated in its aftermath. Fourth, our model fits the data better than Seim's (2006) Nash equilibrium model, especially prior to the shakeout.

[25] An alternative explanation is that, as the industry matures, the focus of strategic play changes from the entry decision to some other decision variable that we do not measure. If this is the case, it is not that Seim's model does better in 2002 but that neither model captures the important strategic decisions after the shakeout. Either way, the statement that little is lost but assuming Seim's model after the shakeout holds.

These latter two results suggest that allowing for heterogeneous ability in empirical models may be most important in the first years of an industry, prior to a shakeout. While our results are only directly informative of the CLEC industry, they suggest that, as an industry matures, little important information may be lost by estimating a standard equilibrium model. This is consistent with laboratory evidence (Chong, Camerer, and Ho 2005; Slonim 2005) suggesting that repeated play leads to higher rationality in games. It is also consistent with List's (2003) field experiments that show that endowment effect biases disappear as players gain experience.

As with any empirical work, this paper has a number of limitations. First, and perhaps most critically, our model assumes that better educated and older managers are better able to conjecture competitor behavior but they are not better at making decisions in other aspects of their firms' operations. While we provide some corroborating evidence that this assumption captures much of the observed variation in our data, we cannot definitively prove its validity. Second, we cannot do a nested test against Nash equilibrium models. Instead, we show that our model fits the data better than one commonly used Nash model (Seim 2006). There are other possible models that we cannot reject (for example, educated experienced managers may be better able to get inside information about what other firms are doing). Still, as discussed above, we rely on laboratory experiments as support for the framework and argue that our results have both internal and external validity. They are also consistent with industry accounts and the underlying patterns in our data. Third, we do not model the decision of the firm owners to hire CEOs. Therefore, our results could be interpreted as saying something about the kinds of firms that hire young, less educated CEOs rather than about the CEOs themselves. On a related note, it is possible that the education and age of CEOs is correlated with the education and age of the other employees and that we are therefore measuring the overall level of education and experience in the company rather than anything to do with the CEO per se. Fourth, we explore a very specific type of ability: the ability to correctly conjecture competitor behavior. We cannot say anything about the many other dimensions of managerial ability. Finally, the empirical setting may differ from the model in ways that may affect the results. For example, while we observe the industry very close to its inception, the game is not truly simultaneous and the extent to which actions are observable may bias our results toward a higher level of ability.

Notwithstanding these limitations, we have provided a structural framework for estimating strategic ability using revealed preference in a real-world setting. The unique solution to this structural model means that we can include manager and firm characteristics in our analysis. Our results help explain several aspects of early competition in local telephone markets. We provide an explanation for why firms run by better educated, older managers operated in markets with fewer competitors. Furthermore, we also show that a Nash model may be a reasonable approximation of the industry after the shakeout occurred.

References

Ai, Chunrong, and Edward C. Norton. 2003. Interaction terms in logit and probit models. *Economics Letters* 80: 123-129.

Ackerberg, Daniel A., Michael H. Riordan, Gregory L. Rosston, and Bradley S. Wimmer. 2009. Low-Income Demand for Local Telephone Service: Effects of Lifeline and Linkup. Working paper, UCLA.

Alexander, Donald L., and Robert M. Feinberg. 2004. "Entry in Local Telecommunications Markets." *Review of Industrial Organization*, 25: 107-127

Allison, Paul. 2002. *Missing Data*, Sage Publications: Thousand Oaks, CA.

Aradillas-Lopez, Andres, and Elie Tamer. 2008. "The Identification Power of Equilibrium in Games." *Journal of Business and Economic Statistics,* 26(3): 261-283.

Augereau, Angelique, Shane Greenstein, and Marc Rysman. 2006. "Coordination versus Differentiation in a Standards War: 56K modems." *Rand Journal of Economics*, 37(4): 887-909.

Baker, Malcolm, Richard Ruback, and Jeffrey Wurgler. 2007. "Behavioral Corporate Finance: A Survey." in Espen Eckbo, ed. *Handbook in Corporate Finance: Empirical Corporate Finance*, Elsevier/North Holland, ch. 4: 145-188.

Bernheim, Douglas. 1984. "Rationalizable Strategic Behavior." *Econometrica* 52: 1007-1028.

Bertrand, Marianne, and Antionette Schoar. 2003. "Managing with Style: The effect of managers on firm policies." *Quarterly Journal of Economics*, 118(4): 1169-1208.

Bosch-Domenech, Antoni, Jose G. Montalvo, Rosemarie Nagel, and Albert Satorra. 2002. "One, Two, (Three), Infinity,…: Newspaper and Lab Beauty-Contest Experiments." *American Economic Review,* 92(5): 1687-1701.

Bresnahan, T. F. & P. C. Reiss. 1990. "Entry in Monopoly Markets." *Review of Economic Studies*, 57(4): 531-551.

Bresnahan, T. F. & P. C. Reiss. 1991. "Entry and Competition in Concentrated Markets." *Journal of Political Economy*, 99(5): 977-1009.

Brown, Alexander L., Colin F. Camerer, and Don Lovallo. 2007. "Limited Strategic Thinking in the Field: The Box Office Premium to Unreviewed "Cold Opened" Movies." Working Paper, California Institute of Technology.

Camerer, Colin. 2003. *Behavioral Game Theory: Experiments in Strategic Interaction*, Princeton University Press: Princeton NJ.

Camerer, Colin, Linda Babcock, George Loewenstein, and Richard Thaler. 1997. "Labor Supply of New York City Cab Drivers: One Day At a Time", *Quarterly Journal of Economics*, 112(2): 407-441.

Camerer, Colin F., Teck-Hua Ho and Juin-Kuan Chong. 2004. "A Cognitive Hierarchy Model of Games." *Quarterly Journal of Economics*, 119(3): 861-898.

Camerer, Colin F., and Eric J. Johnson. 2004. "Thinking About Attention in Games: Backward and Forward Induction." In *The Psychology of Economic Decisions*, edited by I. Brocas and J. Carillo. New York: Oxford University Press.

Che, Hai, K. Sudhir, and P.B. Seetharaman. 2007. "Bounded Rationality in Pricing Under State-Dependent Demand: Do Firms Look Ahead? How Far Ahead?" *Journal of Marketing Research,* 44(3): 434-449.

Chevalier, Judith, A. and Glenn Ellison. 1999. "Are Some Mutual Fund Managers Better than Others? Cross-sectional Patterns in Behavior and Performance", *Journal of Finance*, 54(3): 875-899.

Chong, Juin-Kuan, Colin F. Camerer, and Teck-Hua Ho. 2005. "Cognitive Hierarchy: A Limited Thinking Theory in Games." in R. Zwick and A. Rapoport (eds.), *Experimental Business Research V. III:* 203-228.

Ciliberto, Federico, and Elie Tamer. 2009. "Market Structure and Multiple Equilibria in Airline Markets." *Econometrica* 77(6): 1791-1828.

Collard-Wexler, Allan. 2008. "Comment on Andres Aradillas-Lopez and Elie Tamer." *Journal of Business and Economic Statistics* 26(3): 303-307.

Conlin, Michael, Ted O'Donoghue, and Timothy J. Vogelsang. 2007. "Projection Bias in Catalog Orders." *American Economic Review*, 97(4): 1217–1249.

Costa-Gomes, Miguel A., and Vincent P. Crawford. 2006. "Cognition and Behavior in Two-Person Guessing Games: An Experimental Study." *American Economic Review*, 96(5): 1737-1768.

Crandall, Robert W. (2005), *Competition and Chaos: US Telecommunications since the 1996 Telecom Act*, Brookings Institution Press, Washington DC.

DellaVigna, Stefano. 2009. "Psychology and Economics: Evidence from the Field." *Journal of Economic Literature* 47(2): 315-372

DellaVigna, Stefano and Ulrike Malmendier. 2004. "Contract Design and Self-Control: Theory and Evidence." *Quarterly Journal of Economics*, 119: 353-402.

DellaVigna, Stefano and Ulrike Malmendier. 2006. "Paying Not to Go to the Gym." *American Economic Review*, 96(3): 694-719.

Dunne, Timothy, Mark J. Roberts, and Larry Samuelson. 1988. "Patterns of Firm Entry and Exit in U.S. Manufacturing Industries." *RAND Journal of Economics* 19(4): 495-515.

Economides, Nicholas, Katja Seim, and V. Brian Viard. 2008. "Quantifying the Benefits of Entry into Local Telephone Service." R*AND Journal of Economics* 39: 699-730.

Ellison, Glenn. 2006. "Bounded Rationality in Industrial Organization" in Blundell, Newey and Persson (eds.), *Advances in Economics and Econometrics: Theory and Applications*, Ninth World Congress, Cambridge University Press.

Esponda, Ignacio. 2008. "Behavioral Equilibrium in Economies with Adverse Selection." *American Economic Review*, 98(4): 1269-91.

Federal Communications Commission (1999), "Local Competition: August 1999", Washington DC.

Gabaix, Xavier, and David Laibson. 2006. "Shrouded Attributes, Consumer Myopia, and Information Suppression in Competitive Markets." *Quarterly Journal of Economics*, 121(2): 505—540.

Genesove, David and Christopher Mayer. 2001. "Loss Aversion and Seller Behavior: Evidence from the Housing Market." *Quarterly Journal of Economics*, 116(4): 1233-1260.

Goldfarb, Avi, and Botao Yang. 2009. "Are all managers created equal?" *Journal of Marketing Research*. 46(5): 612-622.

Goldstein, Fred R. 2005. *The Great Telecom Meltdown*. Artech House: Norwood, MA.

Greenstein, S. and M.J. Mazzeo. 2006. "The Role of Differentiation Strategy in Local Telecommunication Entry and Market Evolution: 1999-2002", *Journal of Industrial Economics* 54 (3): 323-350.

Griliches, Zvi. 1986. Economic Data Issues. Chapter 25 in *Handbook of Econometrics v III*. Eds. Z. Griliches and M.D. Intriligator: 1465-1514.

Haile, Philip A., Ali Hortacsu, and Grigory Kosenok. 2008. "On the Empirical Content of Quantal Response Equilibrium." *American Economic Review*, 98(1): 180-200.

Holmes, Thomas J., & Schmitz, James A. Jr. 1995. "On the Turnover of Business Firms and Business Managers." *Journal of Political Economy* 103(5): 1005-1038.

Hortacsu, Ali, and Steven L. Puller. 2008. "Understanding Strategic Bidding in Multi-Unit Auctions: A Case Study of the Texas Electricity Spot Market." *RAND Journal of Economics* 39(1): 86-113.

Hossain, Tanjim and John Morgan. 2006. "...Plus Shipping and Handling: Revenue (Non) Equivalence in Field Experiments on eBay." *Advances in Economic Analysis & Policy*, 6(2): 1429-1429

Jia, Panle. 2008. "What Happens When Wal-Mart Comes to Town? A Empirical Analysis of the Discount Retail Industry." *Econometrica*, 76: 1317-1373.

Kaplan, Steven N., Mark M. Klebanov, and Morten Sorensen. 2008. "Which CEO characteristics and abilities matter?" NBER working paper #14195.

Klepper, Steven. 2002. "Firm survival and the evolution of oligopoly." *RAND Journal of Economics* 33(1): 37-61.

Laibson, David, Andrea Repetto, and Jeremy Tobacman. 2009. "Estimating Discount Functions with Consumption Choices over the Lifecycle." *American Economic Review*, Forthcoming.

Lim, Noah, and Teck-Hua Ho. 2007. "Designing Price Contracts for Boundedly Rational Customers: Does the Number of Blocks Matter?" *Marketing Science* 26(3): 312-26.

List, John A. 2003. "Does Market Experience Eliminate Market Anomalies?" *Quarterly Journal of Economics*, 118(1): 41-71.

Malmendier, Ulrike, and Geoffrey Tate. 2008. "Who Makes Acquisitions? CEO Overconfidence and the Market's Reaction." *Journal of Financial Economics*, 89(1): 20-43.

Malmendier, Ulrike, and Geoffrey Tate. 2005. "CEO Overconfidence and Corporate Investment." *Journal of Finance*, 60(6): 2661-2700.

Mazzeo, M. J. 2002. "Product Choice and Oligopoly Market Structure." *RAND Journal of Economics* 33(1): 221-242.

McKelvey, Richard, and Thomas Palfrey. 1995. "Quantal Response Equilibria for Normal-Form Games." *Games and Economic Behavior*, 10: 6-38.

Mini, Federico. 2001. "The Role of Incentives for Opening Monopoly Markets: Comparing GTE and BOC Cooperation with Local Entrants", *Journal of Industrial Economics* 49(3): 379-414.

Mobius, Markus. 2001. "Death Through Success: The Rise and Fall of Local Service Competition at the Turn of the Century." Working paper, Harvard University.

Oster, Sharon M., and Fiona M. Scott Morton. 2005. "Behavioral Biases Meet the Market: The Case of Magazine Subscription Prices." *Advances in Economic Analysis and Policy* 5(1): Article 1.

Paserman, M. Daniele. 2008. "Job Search and Hyperbolic Discounting: Structural Estimation and Policy Evaluation", *Economic Journal*. 118(531): 1418-1452.

Seim, Katja. 2006. "An Empirical Model of Firm Entry with Endogenous Product-Type Choices." *RAND Journal of Economics* 37(3): 619-640.

Simonsohn, Uri. 2009. "eBay's Crowded Evenings: Competition Neglect in Market Entry Decisions". *Management Science,* Forthcoming.

Simonsohn, U. & Ariely D. 2008. "When Rational Sellers Face Non-Rational Consumers: Evidence from Herding on eBay." *Management Science* 54(9): 1624-1637

Slonim, Robert L. 2005. "Competing Against Experienced and Inexperienced Players." *Experimental Economics*, 8: 55-75.

Spiegler, Ran. 2006. "The Market for Quacks." *Review of Economic Studies*, 73(4): 1113-1131.

Table 1a: Descriptive Statistics by CLEC

Variable	1998 Mean	1998 Std Dev	2002 Mean	2002 Std Dev
# markets to enter	61.5	66.9	90.3	70.6
# markets entered	4.9	9.4	15.7	16.8
Firm age	7.9	17.9	10.3	14.9
Subsidiary	0.312	0.465	0.218	0.416
Privately owned	0.645	0.480	0.625	0.487
Financed by venture capital	0.177	0.383	0.296	0.460
Employees (in thousands) 1998 (N=81)	3.517	16.71	N/A	
Survive to 2002	0.427	0.497	N/A	
Alternate definition of survive to 2002	0.667	0.474	N/A	
Revenue 2002 (million $, N=48)	535	1550	N/A	
Local phone revenue 2002 (million $, N=46)	150	362	N/A	
Manager characteristics (with imputations)				
Age	47.1	8.8	49.2	8.9
Experience	17.7	9.3	20.3	11.3
Any degree from US News top 25 school	0.166	0.364	0.149	0.3378
Any graduate degree	0.554	0.475	0.501	0.469
Any economics or business degree	0.660	0.451	0.655	0.444
Any engineering or science degree	0.364	0.463	0.339	0.443
# of observations (CLECs)	96		83	

Table 1b: Descriptive statistics by market (N=234)

Variable	Mean	Std Dev	Min	Max
Population (in thousands)	224.1	160.8	100.3	951.3
% African American	17.8	18.0	0.3	84.0
Median age	32.8	3.1	22.9	41.8
Household size	2.6	0.418	2.03	4.55
% foreign born	15.6	12.5	1.1	72.1
Median household income (in $1000)	41.7	11.7	23.5	88.8
% below poverty line	14.5	6.3	2.2	35.6
GTE	0.107	0.310	0	1
RBOC	0.808	0.395	0	1
# of establishments in thousands	4.7	3.8	0.661	24.5
Average # of employees / establishment	16.9	5.0	8.18	58.0
% establishments in manufacturing	18.1	10.3	0.001	60.36
# of operating CLECs	2.02	2.9	0	18
# of potential entrants	25.2	7.2	8	35

Table 1c: Descriptive statistics by CLEC-market

	1998		2002	
	Mean	**Std Dev**	**Mean**	**Std Dev**
Entry	0.080	0.271	0.173	0.378
Population (in thousands)	222.4	160.8	229.0	165.7
% African American	16.9	17.0	18.8	17.9
Median age	32.8	3.1	32.9	3.1
Household size	2.67	0.440	2.62	0.404
% Foreign born	17.1	13.1	15.6	12.7
Household income (in $1000)	42.3	12.2	41.1	11.7
% below poverty line	14.0	6.3	14.9	6.3
GTE	0.118	0.323	0.109	0.312
RBOC	0.802	0.398	0.806	0.395
# of establishments in thousands	4.62	3.83	4.87	3.89
Average # of employees / establishment	16.7	5.2	16.8	4.8
% establishments in manufacturing	18.0	10.5	18.1	10.5
Privately owned	0.432	0.495	0.439	0.496
Financed by venture capital	0.160	0.367	0.269	0.443
Firm age	13.7	27.3	12.9	21.8
Subsidiary	0.211	0.408	0.182	0.386
Age	47.2	10.1	48.8	7.46
Experience	17.9	8.5	18.9	10.1
Undergrad from US News top 25	0.111	0.314	0.137	0.340
Any graduate degree	0.670	0.459	0.479	0.491
Any economics or business degree	0.675	0.458	0.716	0.442
Any engineering or science Degree	0.301	0.447	0.354	0.469
# of observations (CLEC-markets)	5906		6095	

Table 2: Logit regressions of 1998 entry on manager characteristics

		(1)	(2)	(3)	(4)	(5)
(1)	**# of competitors × Manager age**	-0.003	-0.009***	-0.013***	-0.011***	-0.018***
(2)	**# of competitors × UG top 25**	-0.127***	-0.193***	-0.250***	-0.228***	-0.372***
(3)	**Manager age**	0.058***	0.066***	0.110***	0.072***	-0.280
(4)	**UG top 25**	0.668***	1.088***	1.406***	1.131***	-2.623
(5)	**# of competitors**	0.123	0.493***	0.703***	0.597***	0.952***
(6)	**Place population in millions**	-0.658	-0.297	-0.231	-0.271	-4.327
(7)	**% black**	0.012***	0.011**	0.010**	0.011**	-0.058*
(8)	**Median age**	-0.081***	-0.0740***	-0.076***	-0.074***	-0.457**
(9)	**Household size**	-1.144***	-1.188***	-1.151***	-1.194***	-1.430
(10)	**% foreign born**	-0.005	-0.002	-0.004	-0.003	0.020
(11)	**HH income in $1000**	-0.020	-0.014	-0.014	-0.014	-0.099
(12)	**% below poverty line**	0.034	0.042*	0.045*	0.043*	-0.140
(13)	**GTE**	0.879***	0.858***	0.834**	0.868***	0.791**
(14)	**RBOC**	0.736***	0.694**	0.728***	0.710***	0.678**
(15)	**# of establishments in thousands**	0.236***	0.214***	0.210***	0.210***	0.284
(16)	**Average # of employees per establishment**	0.036***	0.035***	0.036***	0.035***	0.040
(17)	**% establishments in manufacturing**	-0.017**	-0.015**	-0.016*	-0.015**	0.025
(18)	**# competitors × Log (firm age)**		0.002	-0.0100	-0.0003	-0.011
(19)	**# competitors × Subsidiary**		-0.011	0.072	0.041	0.082*
(20)	**# competitors × Privately owned**		-0.115**	-0.165***	-0.116**	-0.175***
(21)	**# competitors × Venture capital**		-0.061	0.009	-0.011	0.014
(22)	**Log (firm age)**		0.330***	0.405***	0.297***	0.397***
(23)	**Subsidiary**		-1.053***	-1.378***	-1.138***	-1.470***
(24)	**Privately owned**		-0.233	0.277	-0.247	0.311
(25)	**Venture capital**		0.375	0.395	0.358	0.402
(26)	**# competitors × Experience under 10 years**			0.260***		0.269***
(27)	**# competitors × Experience over 20 years**			0.042		0.042
(28)	**# competitors × Degree in econ. or business**			-0.099**	-0.041	-0.103**
(29)	**# competitors × Degree in eng. or science**			-0.088**	-0.075*	-0.099**
(30)	**# competitors × Graduate degree**			0.157***	0.124***	0.163***
(31)	**# competitors × Experience in years**				-0.003	
(32)	**Experience under 10 years**			-2.067***		-2.296***
(33)	**Experience over 20 years**			-1.073***		-1.070***
(34)	**Degree in economics or business**			0.737***	0.127	0.720***
(35)	**Degree in engineering or science**			-0.187	-0.210	-0.108
(36)	**Graduate degree**			-0.563***	-0.263	-0.616***
(37)	**Experience in years**				0.005	
(38)	**Manager age × Place population in millions**					0.086
(39)	**Manager age × % black**					0.001*
(40)	**Manager age × Median age**					0.007*
(41)	**Manager age × Household size**					0.002
(42)	**Manager age × % foreign born**					-0.0004
(43)	**Manager age × HH income in $1000**					0.002
(44)	**Manager age × % below poverty line**					0.004
(45)	**Manager age × # of estabs. in thousands**					-0.002
(46)	**Manager age × Average # employees per estab.**					-0.00004
(47)	**Manager age × % estabs. in manufacturing**					-0.0007
(48)	**UG top 25 × Place population in millions**					-2.428
(49)	**UG top 25 × % black**					0.041**
(50)	**UG top 25 × Median age**					0.148
(51)	**UG top 25 × Household size**					1.961
(52)	**UG top 25 × % foreign born**					-0.045
(53)	**UG top 25 × HH income in $1000**					-0.103
(54)	**UG top 25 × % below poverty line**					-0.130
(55)	**UG top 25 × # of estabs. in thousands**					0.201
(56)	**UG top 25 × Average # employees/estab.**					-0.005
(57)	**UG top 25 × % estabs. in manufacturing**					-0.027
(58)	**Constant**	-2.051	-3.381*	-5.500***	-3.561**	14.548
(59)	**Observations**	5906	5906	5906	5906	5906
(60)	**Log Likelihood**	-1287.2	-1211.0	-1172.2	-1197.5	-1150.0

*significant at 90% confidence level. **significant at 95% confidence level. ***significant at 99% confidence level. Standard errors provided in the appendix. To address concerns expressed in Ai and Norton (2003), we confirmed that marginal effects at mean values yield the same sign as the interaction terms.

Table 3: Reduced form Logit regressions of survival on manager characteristics

		(1)	(2)	(3)	(4)
		Conditional on entry		All Observations	
(1)	**Manager age**	0.009 (0.026)	0.005 (0.027)	-0.022 (0.006)**	-0.022 (0.006)**
(2)	**Manager attended US News top 25 for college**	-0.644 (0.432)	-0.619 (0.465)	1.434 (0.114)**	1.417 (0.115)**
(3)	**Experience under 10 years**	-2.333 (0.825)**	-2.271 (0.839)**	-0.782 (0.122)**	-0.758 (0.123)**
(4)	**Experience over 20 years**	-0.377 (0.345)	-0.301 (0.348)	-0.177 (0.076)*	-0.193 (0.076)*
(5)	**Manager has degree in economics or business**	-1.845 (0.304)**	-1.906 (0.314)**	-1.502 (0.082)**	-1.538 (0.082)**
(6)	**Manager has degree in engineering or science**	-1.235 (0.347)**	-1.246 (0.349)**	0.574 (0.080)**	0.566 (0.081)**
(7)	**Manager has graduate degree**	-0.195 (0.304)	-0.271 (0.319)	-0.527 (0.085)**	-0.552 (0.086)**
(8)	**Log (firm age)**	0.900 (0.146)**	0.9405 (0.149)**	0.549 (0.033)**	0.562 (0.033)**
(9)	**Subsidiary**	0.911 (0.431)*	0.894 (0.444)*	-0.585 (0.091)**	-0.602 (0.092)**
(10)	**Privately owned**	-0.596 (0.449)	-0.597 (0.459)	-0.807 (0.090)**	-0.822 (0.090)**
(11)	**Venture capital**	2.867 (0.616)**	2.836 (0.627)**	1.024 (0.110)**	1.000 (0.110)**
(12)	**# of competitors**	0.019 (0.028)	0.053 (0.052)	-0.009 (0.011)	0.030 (0.021)
(13)	**Place population in millions**		-0.192 (1.436)		0.136 (0.463)
(14)	**% black**		0.009 (0.011)		0.004 (0.003)
(15)	**Median age**		-0.024 (0.064)		0.016 (0.014)
(16)	**Household size**		0.056 (0.767)		-0.020 (0.128)
(17)	**% foreign born**		0.014 (0.019)		0.016 (0.004)**
(18)	**HH income in $1000**		0.0197 (0.033)		0.010 (0.005)*
(19)	**% below poverty line**		-0.023 (0.061)		0.008 (0.011)
(20)	**GTE**		0.389 (0.736)		0.197 (0.143)
(21)	**RBOC**		0.147 (0.596)		-0.062 (0.119)
(22)	**# of establishments in thousands**		-0.036 (0.075)		-0.033 (0.025)
(23)	**Average # of employees per establishment**		0.011 (0.038)		-0.002 (0.007)
(24)	**% establishments in manufacturing**		0.007 (0.017)		0.002 (0.003)
(25)	**Constant**	-0.579 (1.524)	-0.711 (4.045)	1.603 (0.304)**	0.362 (0.870)
(26)	**Log Likelihood**	-238.4	-235.0	-3289.4	-3259.3
(27)	**# of observations**	472	472	5906	5906

For this table and all following tables, standard errors are reported in parentheses. *significant at 90% confidence level. **significant at 95% confidence level. ***significant at 99% confidence level. To address concerns expressed in Ai and Norton (2003), we confirmed that marginal effects at mean values yield the same sign as the interaction terms.

Table 4: Strategic ability and entry coefficients (N=5906)

		Variables	(1) Main	(2) Alternative functional form $\tau_j = K\Phi(\gamma_0 + Z_j\gamma)$	(3) Potential entry means entered by end of 2002	(4) Only places without CAPs in Q4 1994
Coefficients on strategic ability parameter ln(τ)	(1)	Manager age	0.085 (0.021)***	0.090 (0.021)***	0.088 (0.022)***	0.093 (0.022)***
	(2)	Experience under 10 years	-0.053 (0.046)	-0.051 (0.047)	-0.048 (0.048)	-0.062 (0.049)
	(3)	Experience over 20 years	-0.102 (0.029)***	-0.108 (0.031)***	-0.100 (0.030)***	-0.106 (0.030)***
	(4)	Manager attended US News top 25 for college	0.057 (0.028)**	0.055 (0.029)*	0.060 (0.030)**	0.052 (0.035)
	(5)	Manager has degree in economics or business	0.038 (0.022)*	0.039 (0.024)*	0.036 (0.023)	0.040 (0.026)
	(6)	Manager has degree in engineering or science	-0.036 (0.0234)	-0.036 (0.025)	-0.034 (0.025)	-0.035 (0.026)
	(7)	Manager has graduate degree	-0.014 (0.023)	-0.011 (0.025)	-0.020 (0.025)	-0.031 (0.025)
	(8)	Log (firm age)	0.052 (0.013)***	0.056 (0.014)***	0.051 (0.013)***	0.047 (0.014)**
	(9)	Subsidiary	-0.150 (0.038)***	-0.156 (0.038)***	-0.147 (0.041)***	-0.150 (0.0430)***
	(10)	Privately owned	-0.037 (0.030)	-0.038 (0.032)	-0.039 (0.033)	-0.035 (0.034)
	(11)	Venture capital	0.046 (0.039)	0.048 (0.040)	0.045 (0.040)	0.048 (0.041)
	(12)	Constant in τ	0.766 (0.140)***	-0.677 (0.138)***	0.727 (0.153)***	0.732 (0.160)***
Coefficients on entry	(13)	Expected # of competitors	-0.985 (0.131)***	-0.983 (0.133)***	-0.960 (0.139)***	-0.960 (0.144)***
	(14)	Place population in millions	-3.079 (2.870)	-3.118 (2.890)	-3.264 (2.718)	-5.018 (3.430)
	(15)	% black	0.028 (0.013)**	0.028 (0.013)**	0.029 (0.013)**	0.030 (0.013)**
	(16)	Median age	-0.151 (0.073)**	-0.141 (0.073)*	-0.137 (0.072)*	-0.144 (0.079)*
	(17)	Household size	-2.449 (0.736)***	-2.392 (0.746)***	-2.348 (0.716)***	-2.265 (0.870)***
	(18)	% foreign born	0.037 (0.026)	0.037 (0.026)	0.036 (0.025)	0.036 (0.027)
	(19)	HH income in $1000	-0.002 (0.031)	-0.0002 (0.031)	0.001 (0.030)	0.004 (0.034)
	(20)	% below poverty line	0.101 (0.065)	0.108 (0.065)*	0.106 (0.064)*	0.086 (0.068)
	(21)	GTE	2.022 (0.831)**	2.018 (0.829)**	1.960 (0.807)**	1.890 (0.803)**
	(22)	RBOC	1.244 (0.682)*	1.241 (0.676)*	1.189 (0.660)*	1.161 (0.673)*
	(23)	# of establishments in thousands	0.721 (0.168)***	0.720 (0.171)***	0.727 (0.164)***	0.762 (0.194)***
	(24)	Average # of employees per establishment	0.055 (0.044)	0.056 (0.043)	0.055 (0.041)	0.050 (0.042)
	(25)	% establishments in manufacturing	-0.034 (0.019)***	-0.034 (0.018)*	-0.035 (0.018)*	-0.035 (0.019)*
	(26)	Std. dev. of the market-specific unobservable	1.012 (0.237)***	1.011 (0.237)***	0.962 (0.231)***	0.936 (0.226)***
	(27)	Constant	5.096 (4.145)	4.484 (4.155)	4.273 (4.038)	4.803 (4.599)
	(28)	Mean τ	3.13	3.12	3.09	3.10
	(29)	Minimum τ	2.30	2.18	2.33	2.26
	(30)	Maximum τ	4.00	3.96	3.89	3.94
	(31)	Log Likelihood	-1187.1	-1188.0	-1177.7	-1044.9
	(32)	# of observations	5906	5906	5699	5201
	(33)	# of CLECs	96	96	79	95

Table 5: Firms with a higher τ are more likely to exit the industry early

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Survive in sample to 2002[b]		**Alternative definition of survival to 2002** [b]		**Log revenue in 2002** [c]		**Log local phone revenue in 2002** [c]	
τ [a]	0.249	0.371	0.241	0.414	1.648	1.138	1.661	1.637
	(0.142)*	(0.183)**	(0.134)*	(0.170)**	(0.838)*	(0.971)	(0.865)*	(0.953)*
Log(firm age in 1998)		-0.014		-0.001		0.527		0.585
		(0.024)		(0.023)		(0.140)***		(0.134)***
Log(employees in 1998)		-0.024		-0.063		-0.154		-0.435
		(0.063)		(0.061)		(0.321)		(0.311)
Constant					12.354	11.577	11.301	8.926
					(2.955)***	(3.145)***	(3.034)***	(3.090)***
# of observations	96	90	96	90	48	46	46	44
R^2	N/A	N/A	N/A	N/A	0.08	0.32	0.08	0.39
Log Likelihood	-63.93	-59.14	-59.45	-52.56	N/A	N/A	N/A	N/A

[a] τ is calculated from the coefficients in Table 4 Column 1. [b] Logit regressions. Marginal effects shown. [c] Linear regressions.

Table 6: Results in 1998 and 2002 for our model and for Seim (2006)

			(1)	(2)	(3)	(4)
		Variables	**Our model 1998 data**[a]	**Our model 2002 data**	**Seim (2006) 1998 data**	**Seim (2006) 2002 data**
Coefficients on strategic ability parameter ln(τ)	(1)	**Manager age**	0.085 (0.021)***	0.036 (0.028)	N/A	N/A
	(2)	**Experience under 10 years**	-0.053 (0.046)	0.022 (0.050)	.	.
	(3)	**Experience over 20 years**	-0.102 (0.029)***	-0.121 (0.054)**	.	.
	(4)	**Manager attended US News top 25 for college**	0.057 (0.0278)**	0.062 (0.066)	.	.
	(5)	**Manager has degree in economics or business**	0.038 (0.022)*	0.039 (0.047)	.	.
	(6)	**Manager has degree in engineering or science**	-0.036 (0.023)	0.177 (0.055)***	.	.
	(7)	**Manager has graduate degree**	-0.014 (0.023)	0.017 (0.047)	.	.
	(8)	**Log (firm age)**	0.052 (0.013)***	0.173 (0.057)***	.	.
	(9)	**Subsidiary**	-0.150 (0.038)***	-0.082 (0.053)	.	.
	(10)	**Privately owned**	-0.037 (0.030)	-0.067 (0.044)	.	.
	(11)	**Venture capital**	0.046 (0.039)	0.093 (0.059)	.	.
	(12)	**Constant in τ**	0.766 (0.140)***	0.956 (0.203)***	.	.
Coefficients on entry	(13)	**Expected # of competitors**	-0.985 (0.131)***	-0.675 (0.076)***	-0.517 (0.203)**	-0.315 (0.106)***
	(14)	**Place population in millions**	-3.079 (2.87)	-2.927 (2.109)	-2.184 (1.398)	-3.264 (1.251)***
	(15)	**% black**	0.028 (0.013)**	0.048 (0.012)***	0.019 (0.010)**	0.030 (0.010)***
	(16)	**Median age**	-0.151 (0.073)**	-0.147 (0.060)**	-0.092 (0.045)**	-0.077 (0.036)**
	(17)	**Household size**	-2.449 (0.736)***	-2.041 (0.578)***	-0.881 (0.384)**	-0.725 (0.303)**
	(18)	**% foreign born**	0.037 (0.026)	0.021 (0.016)	0.001 (0.011)	0.005 (0.008)
	(16)	**HH income in $1000**	-0.002 (0.031)	0.025 (0.020)	-0.007 (0.015)	0.002 (0.010)
	(20)	**% below poverty line**	0.101 (0.065)	0.129 (0.049)***	0.032 (0.033)	0.050 (0.027)*
	(21)	**GTE**	2.022 (0.831)**	2.009 (0.779)***	1.104 (0.594)*	0.537 (0.436)
	(22)	**RBOC**	1.244 (0.682)*	1.269 (0.514)**	0.753 (0.488)	0.362 (0.310)
	(23)	**# of establishments in thousands**	0.721 (0.168)***	0.704 (0.109)***	0.482 (0.137)***	0.471 (0.117)***
	(24)	**Average # of employees per establishment**	0.055 (0.044)	0.051 (0.022)**	0.040 (0.021)*	-0.006 (0.025)
	(25)	**% establishments in manufacturing**	-0.034 (0.019)***	-0.024 (0.014)*	-0.014 (0.010)	-0.007 (0.009)
	(26)	**Std. dev. of the market-specific unobservable**	1.012 (0.237)***	1.233 (0.199)***	0.313 (0.242)	0.542 (0.137)***
	(27)	**Constant**	5.096 (4.145)	3.429 (3.246)	1.149 (2.393)	1.586 (1.877)
	(28)	**Mean τ**	3.13	4.65	N/A	N/A
	(29)	**Minimum τ**	2.30	3.11	N/A	N/A
	(30)	**Maximum τ**	4.00	7.37	N/A	N/A
	(31)	**Log Likelihood**	-1187.1	-2291.8	-1286.7	-2340.7
	(32)	**# of observations**	5906	6095	5906	6095

[a]Repeats table 4 column 1

Table 7: Fit comparison with Seim (2006)

		1998	2002
R^2 of regression of entry on predicted entry	**Our model**	0.211	0.169
	Seim (2006)	0.149	0.148
Bayesian Information Criterion	**Our model**	2476.0	4685.8
	Seim (2006)	2630.0	4738.2
Mean Squared Error	**Our model**	0.058	0.117
	Seim (2006)	0.062	0.119

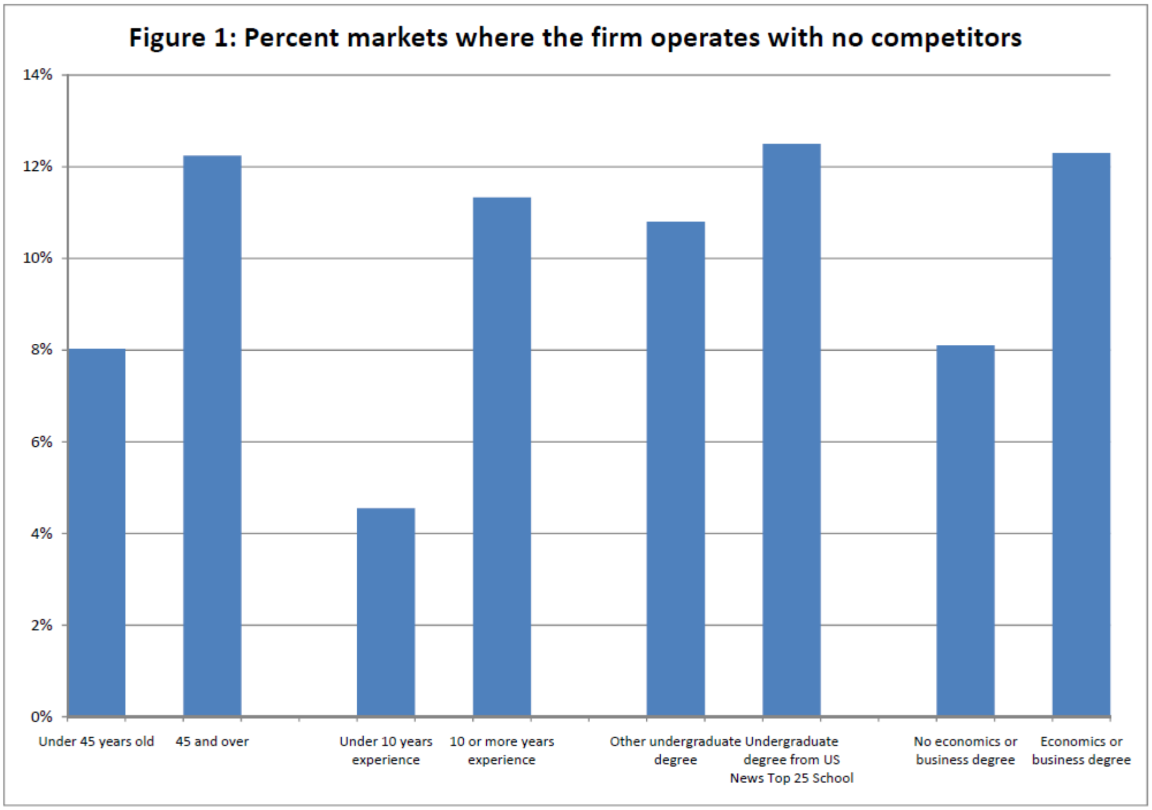


Figure 1: Percent markets where the firm operates with no competitors
14%
12%
10%
8%
6%
4%
2%
0%
Under 45 years old
45 and over
Under 10 years experience
10 or more years experience
Other undergraduate degree
Undergraduate degree from US News Top 25 School
No economics or business degree
Economics or business degree

Appendix to

Who Thinks about the Competition?

Managerial ability and strategic entry in US local telephone markets

Appendix 1: Constructing the Likelihood Function

In this appendix we outline the steps in constructing the simulated likelihood function we use for estimation:

1. Take R random draws from normal distribution $N(0,\sigma_\xi)$ for each market. Let R be 20. Let ξ_m^r denote a single draw r $(r=1,2,...,R)$ for market m.

2. For each draw ξ_m^r and for each firm j at market m, construct $E\left(\overline{\Pi}_{jm}^r \mid k\right)$ iteratively from type 0 to K. For the first two types 0 and 1, we have:

$$E\left(\overline{\Pi}_{jm}^r \mid k=0\right) = \beta_0 + X_m\beta + \xi_m^r \tag{A1.1}$$

$$E\left(\overline{\Pi}_{jm}^r \mid k=1\right) = \beta_0 + X_m\beta + \psi \sum_{i=1,...,J_m}^{i\neq j} \Phi\left(\beta_0 + X_m\beta + \xi_m^r\right) + \xi_m^r \tag{A1.2}$$

   For a type k $(k \geq 2)$ player, let $\Pr(l \mid \tau_i, k-1)$ denote her perceived probability of competitor i being type l, $l \leq k-1$. According to the truncated Poisson distribution $Poisson(\tau_i, k-1)$, we can derive: $\Pr(l \mid \tau_i, k-1) = \dfrac{\tau_i^{\,l} e^{-\tau_i}/l!}{\sum_{h=0}^{k-1} \tau_i^{\,h} e^{-\tau_i}/h!}$. For $k \geq 2$, we have:

$$E\left(\overline{\Pi}_{jm}^r \mid k\right) = \beta_0 + X_m\beta + \psi \sum_{i=1,...,J_m}^{i\neq j} \Phi\left\{\sum_{l=0}^{k-1}\left[E\left(\overline{\Pi}_{jm}^r \mid l\right) \times \Pr\left(l \mid \tau_i, k-1\right)\right]\right\} + \xi_m^r \tag{A1.3}$$

   In (A1.3), we need to use $E\left(\overline{\Pi}_{jm}^r \mid k\right)$, $(k=0,1...,k-1)$ from the iterative process.

3. With $E\left(\overline{\Pi}_{jm}^r \mid k\right)$, we can write: $\Pr\left(D_{jm}^r = 1 \mid k\right) = \Phi\left(E\left(\overline{\Pi}_{jm}^r \mid k\right)\right)$.

4. Construct entry probability of firm j unconditional on types. We know a firm's type is drawn from $Poisson(\tau_j)$ with no truncation, where $\tau_j = \exp(\gamma_0 + Z_j\gamma)$. Let $\Pr(k \mid \tau_j)$ denote the true probability of firm j being type k. We then have:

$$prob\left(D_{jm}^r = 1\right) = \Phi\left\{\sum_{k=0}^{K}\left[E\left(\overline{\Pi}_{jm}^r \mid k\right) \times \Pr\left(k \mid \tau_j\right)\right]\right\} \tag{A1.5}$$

5. Construct $prob\left(D_{jm}^r = 1\right)^{D_{jm}} prob\left(D_{jm}^r = 0\right)^{1-D_{jm}}$, where D_{jm} is a vector of actual entry decisions we observe in data and $prob\left(D_{jm}^r = 0\right) = 1 - prob\left(D_{jm}^r = 1\right)$.

6. Finally, with $prob\left(D_{jm}^r = 1\right)^{D_{jm}} prob\left(D_{jm}^r = 0\right)^{1-D_{jm}}$ we can construct equation (6) in the main text:

$$\ln L_{simulated} = \sum_{m=1,...,M} \ln\left\{\frac{1}{R}\sum_{r=1}^{R}\left[\prod_{j=1}^{J_m}\left(prob\left(D_{jm}^r = 1\right)^{D_{jm}} prob\left(D_{jm}^r = 0\right)^{1-D_{jm}}\right)\right]\right\}$$

APPENDIX 2: TABLES AND FIGURE

Appendix Table 2.1: Include standard errors from Table 2

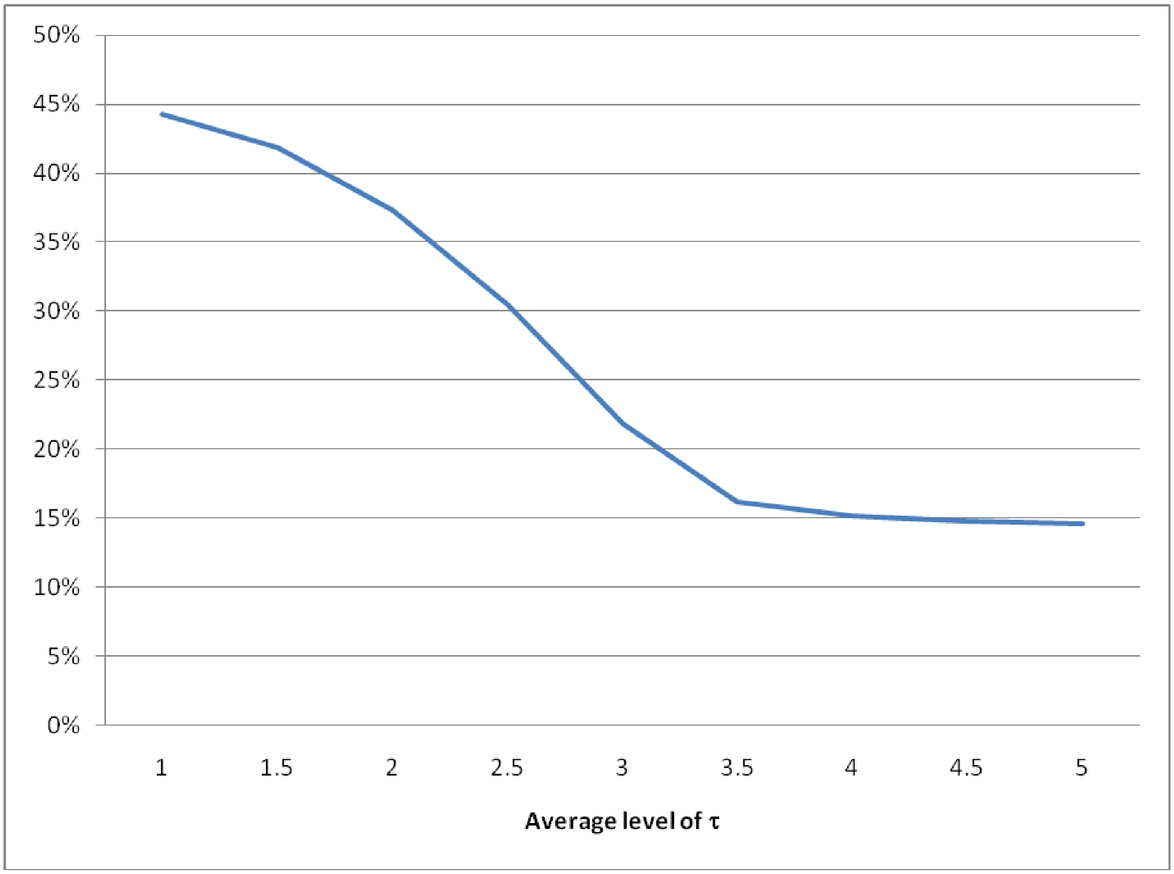
	(1)	(2)	(3)	(4)	(5)
COMPETITION BY CORE MANAGER CHARACTERISTICS					
# of competitors × Manager age	-0.0029	-0.0088	-0.0134	-0.0107	-0.0181
	(0.0018)	(0.0025)***	(0.0031)***	(0.0032)***	(0.0048)***
# of competitors × Manager attended US News top 25 for college	-0.1272	-0.1931	-0.2504	-0.2281	-0.3722
	(0.0467)***	(0.0546)***	(0.0568)***	(0.0563)***	(0.1197)***
CORE MANAGER CHARACTERISTICS					
Manager age	0.0582	0.0664	0.1100	0.0718	-0.2799
	(0.0106)***	(0.0139)***	(0.0165)***	(0.0169)***	(0.2252)
Manager attended US News top 25 for college	0.6680	1.0880	1.4061	1.1312	-2.6229
	(0.2462)***	(0.2837)***	(0.2935)***	(0.2897)***	(6.3627)
MARKET CHARACTERISTICS					
# of competitors	0.1232	0.4927	0.7029	0.5966	0.9515
	(0.0921)	(0.1465)***	(0.1762)***	(0.1699)***	(0.2572)***
Place population in millions	-0.6578	-0.2969	-0.2318	-0.2710	-4.3272
	(0.6435)	(0.6693)	(0.6819)	(0.6748)	(5.1877)
% black	0.0122	0.0107	0.0097	0.0108	-0.0578
	(0.0044)***	(0.0045)**	(0.0045)**	(0.0045)**	(0.0341)*
Median age	-0.0807	-0.0739	-0.0760	-0.0739	-0.4566
	(0.0254)***	(0.0259)***	(0.0263)***	(0.0260)***	(0.1936)*
Household size	-1.1440	-1.1882	-1.1506	-1.1937	-1.4298
	(0.2861)***	(0.2918)***	(0.2935)***	(0.2940)***	(2.1058)
% foreign born	-0.0047	-0.0024	-0.0041	-0.0026	0.0196
	(0.0077)	(0.0078)	(0.0080)	(0.0079)	(0.0572)
HH income in $1000	-0.0196	-0.0143	-0.0139	-0.0136	-0.0988
	(0.0134)	(0.0135)	(0.0137)	(0.0136)	(0.0999)
% below poverty line	0.0344	0.0417	0.0452	0.0425	-0.1404
	(0.0243)	(0.0247)*	(0.0249)*	(0.0248)*	(0.1843)
GTE	0.8790	0.8583	0.8338	0.8680	0.7911
	(0.3224)***	(0.3261)***	(0.3296)**	(0.3275)***	(0.3310)**
RBOC	0.7360	0.6936	0.7283	0.7096	0.6779
	(0.2686)***	(0.2717)**	(0.2747)***	(0.2726)***	(0.2763)**
# of establishments in thousands	0.2355	0.2141	0.2099	0.2099	0.2841
	(0.0346)***	(0.0360)***	(0.0367)***	(0.0364)***	(0.2736)
Average # of employees per establishment	0.0360	0.0346	0.0356	0.0350	0.0396
	(0.0115)***	(0.0119)***	(0.0120)***	(0.0120)***	(0.0905)
% establishments in manufacturing	-0.01657	-0.0150	-0.0157	-0.0146	0.0249
	(0.0068)**	(0.0070)**	(0.0071)**	(0.0070)**	(0.0534)
COMPETITION BY FIRM CHARACTERISTICS					
# of competitors × Log (firm age)		0.0023	-0.0100	-0.0003	-0.0108
		(0.0144)	(0.0165)	(0.0163)	(0.0167)
# of competitors × Subsidiary		-0.0109	0.0716	0.0412	0.0824
		(0.0426)	(0.0479)	(0.0464)	(0.0491)*
# of competitors × Privately owned		-0.1146	-0.1645	-0.1159	-0.1750
		(0.0458)**	(0.0499)***	(0.0479)**	(0.0508)***
# of competitors × Venture capital		-0.0606	0.0093	-0.0109	0.0140
		(0.0523)	(0.0574)	(0.0554)	(0.0577)
FIRM CHARACTERISTICS					
Log (firm age)		0.3297	0.4048	0.2966	0.3973
		(0.0741)***	(0.0868)***	(0.0811)***	(0.0885)***
Subsidiary		-1.0527	-1.3784	-1.1383	-1.4702
		(0.2642)***	(0.2899)***	(0.2806)***	(0.2997)***
Privately owned		-0.2325	0.2773	-0.2466	0.3106
		(0.2687)	(0.2838)	(0.2767)	(0.2896)
Venture capital		0.3751	0.3951	0.3577	0.4020
		(0.3202)	(0.3408)	(0.3363)	(0.3414)
COMPETITION BY OTHER MANAGER CHARACTERISTICS					
# of competitors × Experience under 10 years			0.2601		0.2685
			(0.0759)***		(0.0768)***
# of competitors × Experience over 20 years			0.0415		0.0417
			(0.0369)		(0.0373)
# of competitors × Manager has degree in economics or business			-0.0992	-0.0410	-0.1033
			(0.0401)**	(0.0402)	(0.0412)**
# of competitors × Manager has degree in engineering or science			-0.0878	-0.0750	-0.0989
			(0.0437)**	(0.0438)*	(0.0448)**
# of competitors × Manager has graduate degree			0.1573	0.1242	0.1630
			(0.0405)***	(0.0420)***	(0.0412)***

# of competitors × Experience in years				-0.0028	
				(0.0024)	
OTHER MANAGER CHARACTERISTICS					
Experience under 10 years			-2.0666		-2.2955
			(0.5155)***		(0.5379)***
Experience over 20 years			-1.0728		-1.0700
			(0.2216)***		(0.2253)***
Manager has degree in economics or business			0.7371	0.1273	0.7201
			(0.2164)***	(0.2138)	(0.2219)***
Manager has degree in engineering or science			-0.1867	-0.2104	-0.1079
			(0.2292)	(0.2355)	(0.2323)
Manager has graduate degree			-0.5632	-0.2625	-0.6155
			(0.2088)***	(0.2268)	(0.2136)***
Experience in years				0.0047	
				(0.0135)	
MANAGER AGE-PLACE DEMOGRAPHICS INTERACTIONS					
Manager age × Place population in millions					0.0858
					(0.1011)
Manager age × % black					0.0013
					(0.0007)*
Manager age × Median age					0.0073
					(0.0038)*
Manager age × Household size					0.0023
					(0.0409)
Manager age × % foreign born					-0.0004
					(0.0011)
Manager age × HH income in $1000					0.0018
					(0.0019)
Manager age × % below poverty line					0.0039
					(0.0036)
Manager age × # of establishments in thousands					-0.0018
					(0.0054)
Manager age × Average # of employees per establishment					-0.0000
					(0.0017)
Manager age × % establishments in manufacturing					-0.0007
					(0.0010)
MANAGER ATTENDED UNDERGRAD AT US NEWS TOP 25- PLACE DEMOGRAPHICS INTERACTIONS					
Manager UG top 25 × Place population in millions					-2.4284
					(2.5965)
Manager UG top 25 × % black					0.0408
					(0.0161)**
Manager UG top 25 × Median age					0.1484
					(0.0939)
Manager UG top 25 × Household size					1.9605
					(1.2396)
Manager UG top 25 × % foreign born					-0.0447
					(0.0319)
Manager UG top 25 × HH income in $1000					-0.1032
					(0.0656)
Manager UG top 25 × % below poverty line					-0.1304
					(0.0985)
Manager UG top 25 × # of establishments in thousands					0.2011
					(0.1436)
Manager UG top 25 × Average # of employees per establishment					-0.0049
					(0.0544)
Manager UG top 25 × % establishments in manufacturing					-0.0271
					(0.0257)
Constant	-2.0508	-3.3812	-5.5001	-3.5608	14.5478
	(1.5989)	(1.7333)*	(1.8069)***	(1.7679)**	(11.5848)
# of Observations	5906	5906	5906	5906	5906
Log Likelihood	-1287.2	-1211.0	-1172.2	-1197.5	-1150.0

Appendix Table 2.2: Alternative Covariate Specifications

			(1)	(2)	(3)	(4)
		Variables	**Alternative treatment of missing variables**	**Alternative covariates**	**Only focal manager characteristics**	**Only manager characteristics**
Coefficients on strategic ability parameter ln(□)	(1)	**Manager age**	0.085		0.077	0.082
			(0.0218)***		(0.015)***	(0.016)***
	(2)	**Experience under 10 years**	-0.025	-0.051		-0.060
			(0.051)	(0.045)		(0.043)
	(3)	**Experience over 20 years**	-0.098	-0.129		-0.094
			(0.031)***	(0.029)***		(0.026)***
	(4)	**Manager attended US News top 25 for college**	0.060	0.016	0.053	0.039
			(0.028)**	(0.025)	(0.024)**	(0.026)
	(5)	**Manager has degree in economics or business**	0.035	0.059		-0.005
			(0.023)	(0.022)***		(0.022)
	(6)	**Manager has degree in engineering or science**	-0.033	-0.006		-0.102
			(0.023)	(0.021)		(0.023)***
	(7)	**Manager has graduate degree**	-0.014	-0.017		0.011
			(0.023)	(0.020)		(0.021)
	(8)	**Log (firm age)**	0.048	0.059		
			(0.012)***	(0.012)***		
	(9)	**Subsidiary**	-0.142	-0.117		
			(0.039)***	(0.031)***		
	(10)	**Privately owned**	-0.032	-0.040		
			(0.030)	(0.027)		
	(11)	**Venture capital**	0.037	0.074		
			(0.038)	(0.040)*		
	(12)	**Age under 40**		-0.163		
				(0.039)***		
	(13)	**Age over 55**		0.087		
				(0.025)***		
	(14)	**Missing data dummy**	-0.138			
			(0.083)*			
	(15)	**Constant in τ**	0.774	1.161	0.812	0.871
			(0.145)***	(0.074)***	(0.106)***	(0.103)***
Coefficients on entry	(16)	**Expected # of competitors**	-1.008	-1.070	-0.820	-0.920
			(0.141)***	(0.132)***	(0.106)***	(0.116)***
	(17)	**Place population in millions**	-3.321	-2.970	-1.298	-2.214
			(2.938)	(3.209)	(2.121)	(2.704)
	(18)	**% black**	0.0290	0.025	2.994	0.030
			(0.013)**	(0.014)*	(1.033)***	(0.012)***
	(16)	**Median age**	-0.145	-0.150	-0.134	-0.104
			(0.073)**	(0.078)*	(0.061)**	(0.064)
	(20)	**Household size**	-2.446	-2.410	-2.079	-2.253
			(0.747)**	(0.814)***	(0.597)***	(0.634)***
	(21)	**% foreign born**	0.039	0.041	1.246	0.028
			(0.026)	(0.027)	(1.659)	(0.023)
	(22)	**HH income in $1000**	-0.003	0.001	0.002	-0.012
			(0.031)	(0.036)	(0.022)	(0.029)
	(23)	**% below poverty line**	0.104	0.130	7.774	0.068
			(0.066)	(0.073)*	(4.773)	(0.057)
	(24)	**GTE**	2.009	2.454	2.100	2.390
			(0.839)**	(0.892)***	(0.732)***	(0.752)***
	(25)	**RBOC**	1.245	1.234	1.497	1.842
			(0.690)*	(0.731)*	(0.641)**	(0.617)***
	(26)	**# of establishments in thousands**	0.739	0.766	0.576	0.654
			(0.174)***	(0.185)***	(0.120)***	(0.151)***
	(27)	**Average # of employees per establishment**	0.055	0.064	0.054	0.060
			(0.044)	(0.046)	(0.032)*	(0.035)*
	(28)	**% establishments in manufacturing**	-0.034	-0.038	-3.343	-0.027
			(0.019)*	(0.020)*	(1.428)**	(0.017)
	(29)	**Std dev of the market-specific unobservable**	1.012	1.231	0.656	0.944
			(0.244)***	(0.257)***	(0.221)***	(0.234)***
	(30)	**Constant**	4.941	4.269	3.857	3.296
			(4.163)	(4.605)	(3.289)	(3.470)
	(31)	**Mean τ**	3.13	3.16	3.27	3.27
	(32)	**Minimum τ**	1.70	2.24	2.85	2.70
	(33)	**Maximum τ**	4.01	4.03	3.90	3.90
	(34)	**Log Likelihood**	-1181.8	-1183.0	-1262.6	-1235.2
	(35)	**# of observations**	5906	5906	5906	5906

Appendix Figure 2.3: Percent of decisions with ex post regret



In order to construct this figure, we simulate what would happen if strategic ability was higher or lower than estimated. In particular, we add or subtract a constant from the estimated value of τ in order to change average value of τ. We then simulate how the CLECs would behave based on these different assumptions and our parameter estimates in table 4 column 1. By "regret", we mean that firms would have made a different decision had they correctly conjectured competitor behavior.