Are All Managers Created Equal?[*]

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Abstract

Some managers are better than others. Based on the cognitive hierarchy framework of Camerer, Ho, and Chong (2004), the authors develop a structural econometric model that estimates the level of strategic thinking. In the model, firms with a high level of strategic thinking are more likely to correctly conjecture the expected actions of their competitors. The authors apply this model to decisions by managers at 2,233 Internet Service Providers to offer their customers access through 56K modems in 1997. The model is validated by showing that firms with a higher estimated probability of strategic thinking were more likely to have survived through April 2007. The estimation results show considerable heterogeneity in the degree to which firms behave strategically and suggest that strategic ability affects marketing outcomes: a simulated increase in strategic ability means that fewer firms offer the technology to their customers.

Keywords: behavioral IO, technology adoption, service retailing, diffusion, ISP, cognitive hierarchy

1. Introduction

Some managers are better than others. This (perhaps unsurprising) fact is implicit in our teaching of business students and the widespread reporting of good and bad managerial decisions. In order to better understand how management ability affects outcomes, it is necessary to allow for heterogeneity in ability in our models. Nevertheless, while numerous papers model heterogeneous consumers on a variety of dimensions, management heterogeneity is rarely examined. This is not for a lack of models of strategic heterogeneity. For instance, Camerer, Ho, and Chong (2004) develop a "cognitive hierarchy" model (henceforth CH) of heterogeneous strategic thinking where players differ in how deeply they consider competitor choices.[1] They then provide considerable supporting evidence from laboratory experiments. In our paper, we develop the first structural non-laboratory estimate of management heterogeneity based on the CH model and apply it to the decisions of 2,233 Internet Service Providers (ISPs) to provide 56K modem technology to their customers. In particular, based on evidence from laboratory experiments, we build an empirical model where players differ in their ability to correctly conjecture the behavior of their competitors. We then explore the consequences of a change in this ability for ISPs and for modem manufacturers.

Heterogeneity in strategic ability is particularly important in retail markets like the ISP market. Retailers must choose which products to offer their customers, and the benefit of offering a particular product will depend on whether competing retailers also offer that product. Optimal product assortment decisions are therefore dependent on expectations over competitor actions. Strategic thinking by retailers will then also affect manufacturers. Ataman, Mela, and Van Heerde (2008) show that wide distribution may be the most important factor in determining

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[1] Haruvy, Stahl, and Wilson (2001), Ho, Lim, and Camerer (2006), and others discuss a number of other behavioral economic models of player heterogeneity such as McKelvey and Palfrey's (1995) Quantal Response Equilibrium.

the success of a new product. Thus, if strategic ability affects retailer decisions to offer products, it will affect manufacturer outcomes as well.

In this paper, we explore a particular kind of strategic ability: the ability to correctly conjecture competitor actions through step-by-step reasoning. A rich experimental literature has found that the cognitive requirements of finding a Perfect Bayesian Equilibrium are substantial (see Camerer, 2003, for a review). These studies have shown that, rather than solving for the equilibrium, players typically go through a small (and varying) number of iterations on the expected actions of other players (e.g., Costa-Gomes and Crawford, 2006; Stahl and Wilson, 1994). Overall, the experimental evidence on the difficulty of playing these games suggests that small firms with inexperienced managers in a new industry are unlikely to fully solve for the Perfect Bayesian Equilibrium. Since we are studying such an industry, we adapt Camerer, Ho, and Chong's (2004) cognitive hierarchy model to the strategic decisions of ISPs. We operationalize this by modeling a type-0 retailer to act as if it is the only player in the market. A type-1 retailer acts as if it believes all other retailers act as if they are the only player in the market. A type-2 retailer acts as if all other players are distributed between type-0 and type-1. And a type-k retailer acts as if all other players are distributed between type-0 and type-(k-1). This structure enables us to develop a prediction of behavior for players of different types.[2] We then fit these predictions to data to see which distribution of types best explains observed behavior.

Our context for estimating this model is the 1997 decision by ISPs to offer customers a higher speed service (56Kbps over 33Kbps), and if so, which technology to provide. As discussed in Augereau, Greenstein, and Rysman (2006), firms faced a clear, reasonably well-

[2] A useful consequence of this model is that the solution is unique because each firm believes it knows what its competitors are doing but its competitors do not know what it is doing. This overcomes the common problem of multiple equilibria in simultaneous entry games (e.g. Seim 2006; Bajari, Hong, and Ryan 2004).

defined technology choice game between not upgrading, upgrading to Rockwell Semiconductor's K56Flex modem, upgrading to US Robotics' X2 modem, or upgrading to both. We ask (1) How does strategic thinking affect the distribution of 56K modem technology?, (2) Are those players estimated to be more strategic thinkers more likely to survive?, and (3) What factors are correlated with strategic thinking? We find that strategic thinking *slowed* the distribution and diffusion of the new technology, that those ISPs estimated to be more likely to be strategic using 1997 data were more likely to have survived through April 2007, and that firms behaved more strategically if they competed in larger cities, they competed with more firms, and they competed in markets with more educated populations. More broadly, our results provide external validity to the current laboratory research on the CH model: In addition to the finding on survival, our estimate of the parameter that measures the distribution of strategic ability across the population is at the high end of the range found by Camerer, Ho, and Chong (2004).

The early ISP market provides an ideal setting for examining heterogeneity in strategic thinking. In addition to the clear strategic decision described above, many firms competed in a number of local markets. The dial-up nature of the technology means that we can easily define markets by local telephone calling areas. Perhaps because this was a new industry, large firms like AOL co-existed with very small companies run out of people's homes. MBAs and seasoned managers competed against recent computer science graduates who had helped run the modem pools at their universities. Unlike a Perfect Bayesian Equilibrium approach, the CH model can account for this heterogeneity in managerial expertise in the context of simultaneous entry games.[3]

Overall, the CH model helps explain the variation in managerial decision-making in a useful way. Our combination of behavioral game theory with the structural methods of the New Empirical Industrial Organization provides a new framework for understanding variation in the decisions of managers who face similar choices.[4] Without a model of strategic ability, it is not possible to examine how that ability affects market outcomes. Thus, such a model is a necessary step toward our finding that strategic thinking slowed the distribution and diffusion of 56K modem technology, supporting Reinganum (1981) theoretical work on the subject. More strategic managers are *less* likely to adopt new technologies because they anticipate lower profits due to competition.

This suggests an important difference between the diffusion of products to consumers and to businesses: The likelihood of a given firm's adoption of a business product often depends on the behavior of other competing businesses. However, our results suggest that the importance of this effect is heterogeneous across managers with different abilities. For example, strategic considerations may be less important when the product is aimed at a new industry with inexperienced management than at a mature industry with lifetime professional managers.

Next, we review the two key papers on which this research is built: Augereau, Greenstein, and Rysman (2006) provide the main data and the empirical setting, and Camerer, Ho, and

[3] While this decision is not truly simultaneous, Augereau, Greenstein, and Rysman (2006) provide rich detail on why it can be reasonably viewed as a simultaneous game. Much of their evidence comes from differences in adoption between July 1997 and October 1997.

[4] Brown, Camerer, and Lovallo (2007) undertake a similar exercise by comparing quantal response equilibrium, cursed equilibrium, and CH in the context of movie distributors' decisions to show movies to critics. Che, Sudhir, and Seetharaman (2007) and Lim and Ho (2007) also explore the consequences of behavioral assumptions to firms. Other related studies document behavior biases exhibited by real-world managers (Hortacsu and Puller 2007; Chan, Hamilton, and Makler 2007) and develop semi-parametric models of rationalizability (Aradillas-Lopez and Tamer 2008).

Chong (2004) provide the theoretical basis for the model. In section 3, we describe our model and empirical strategy. In section 4, we present our results. Section 5 lists some limitations and section 6 concludes.

2. A Review of Two Key Building Blocks

2.1 56K modem technology and Augereau, Greenstein, and Rysman (2006)

56K modems were introduced in 1997. They allowed data transfer over the Internet at a faster speed than the previous technology at a time when Internet traffic was increasing rapidly. Two modem technologies competed for the market: the X2 modem from US Robotics and the K56Flex modem by Rockwell Semiconductor. These technologies had the same performance capabilities, although they differed in their ease of connection depending on local characteristics. They were also incompatible: A consumer with a given modem could only connect to an ISP at 56K speed if that ISP had the same technology.

Augereau, Greenstein and Rysman (2006) study the choice of 56K modem technology by ISPs. Specifically, ISPs that offered 33K service at a telephone switch decided whether or not to offer 56K service on X2, K56Flex, both, or neither. They model the ISPs' problem as an entry game into two markets and assume a Perfect Bayesian Equilibrium. They then use a bivariate probit model to estimate the parameters and show that ISPs were less likely to adopt the technology that more of their competitors adopted.

Building on Augereau, Greenstein, and Rysman (2006), we model an ISP's technology choice problem as an entry game of imperfect information. Then we use CH theory to capture heterogeneity in ISP use of strategic thinking. We believe the early ISP market is a particularly good industry on which to apply CH theory because: (1) ISP firm managers are likely heterogeneous in experience, reasoning ability, etc., (2) each ISP's payoff depends on competing

ISPs' technology choices, (3) the set of players and markets is well-defined, unlike many other entry-type games, and (4) the decisions were largely made over a three-month period, a period short enough that a simultaneous game might be a reasonable model.

Data and summary statistics

Our main data set is identical to that used in Augereau, Greenstein, and Rysman (2006). Their paper provides a rich description of the data; we briefly describe some key aspects of the data here. Augereau, Greenstein, and Rysman use two ISP directories, *theDirectory* and *Boardwatch*, to collect information on ISP location (through the telephone numbers that could be used to dial in), 56K technology, and some features of the ISP. Following Augereau, Greenstein, and Rysman (2006), we define markets by telephone switches. We consider an ISP to compete in a given switch/market if it is a local telephone call from that switch to the ISP dial-in number. We also have demographic data based mainly on the zip codes associated with each switch. The data consist of 2,233 ISPs in 9,070 markets for a total of 216,186 ISP-market combinations.

Table 1a provides descriptive statistics by market, table 1b provides descriptive statistics by ISP, and table 1c provides descriptive statistics by ISP-market. Most variable names are self-explanatory. The variable *ISP has digital connection* is missing for a number of observations. We include a variable *missing* for these observations to allow us to include the digital connection variable while limiting the effect of the missing data on our results. In section 4.3, we supplement this core data set with information collected by visiting each ISP's URL to determine which of the ISPs still existed in April 2007.

We observe ISPs making one of four adoption choices: 1) adopt neither technology, 2) adopt Rockwell Semiconductor's K56Flex, 3) adopt US Robotics' X2, or 4) adopt both.

Augereau, Greenstein, and Rysman (2006) argue that the decision can be viewed as simultaneous because the diffusion of the technology was so rapid. Table 1c contrasts the adoption rate for the technologies in July and October 1997. Since the bulk of the observed adoptions occur in this short window, they assume that the game can be viewed as simultaneous. We also rely on this assumption. To explore the consequences of this assumption, we estimate a model with the July decisions taken as exogenous and only model changes from July to October. Qualitative results do not change.

The descriptive statistics reveal a further complication: most ISPs operated in multiple markets. The average ISP operated in 96 markets, and the median served 16 (equivalent to one or two local calling areas). No ISP served all switches. Multi-market ISPs operated the same technology in all their markets. This complicates our analysis because we need to alter the standard CH model to address multi-market ISPs and to constrain ISP decisions to be the same across markets. We discuss how we deal with this below.

2.2 Cognitive hierarchy and Camerer, Ho, and Chong (2004)

Suppose many players play a simultaneous-move game where all players' payoffs not only depend on their decision but also on other players' decisions. Players therefore need to form expectations about what the other players will do. While many models allow players to differ in their payoff functions, they typically assume all players have the same ability to think through the game. Camerer, Ho, and Chong (2004) argue that this assumption is flawed. They develop CH theory to allow players to differ in their ability to think strategically.[5] We apply a CH model to our data on ISP decisions.

[5] They show that CH works well in both the entry-type game examined in this paper and in a "*p*-beauty contest" game (Nagel 1995; Ho, Camerer, and Weigelt 1998). In a *p*-beauty contest game, researchers ask a group of players

In CH theory, players have different hierarchies of rationality. Type-0 thinkers do not consider their competitors; a type-1 thinker assumes all competitors are type-0; a type-2 player assumes the other players are a combination of type-0 players and type-1 players; a type-k players assumes the other players are distributed between type-0 and type-(k-1). Camerer, Ho, and Chong (2004) provide evidence that a Poisson distribution effectively describes the observed distribution of players. We rely on this evidence to support our model and identification. In the CH model, a type-k player assumes all other players are distributed truncated Poisson between type-0 and type-(k-1). The model assumes the distribution of types in the population has the same Poisson parameter as the truncated Poisson used by players to assess competitor types.

We interpret this hierarchy of rationality as heterogeneity in strategic ability.[6] Therefore, type-0 managers do not consider competitors. They instead only consider the characteristics of their firm and their market. Given their own characteristics, type-1 players best respond to a situation where all their competitors are type-0. And so on. A key difference between CH and Nash is therefore that in CH models some players will be surprised by the behavior of their competitors because they did not accurately think through their competitor's choices.

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to pick a number from 1 to 100. The player who chooses a number that is closest to 2/3 the average of the numbers chosen by all players wins a cash prize. The Nash equilibrium prediction for this game is that all players will choose the number 1. However, data from diverse subject groups show that the Nash prediction explains first-period choices poorly in this game and that the CH model predicts them quite well (Ho, Lim, and Camerer 2006). We mention the *p*-beauty contest game because two studies using that game also try to explain the distribution of the ability parameter, τ. First, Chong, Camerer, and Ho (2005) regress τ on demographic characteristics and show that higher-quality education is positively correlated with τ. Second, Slonim (2005) shows that experience playing the game matters in predicting performance.

[6] Our interpretation relies on the prior experimental literature that shows players who appear to think strategically show decision processes consistent with this idea. In particular, Bosch-Domenech et al. (AER 2002) showed that players estimated by a k-step thinking model to be strategic thinkers explicitly give logic based on step-thinking. In other work, Camerer and Johnson (2004) and Costa-Gomes, Crawford, and Broseta (2001) showed that players estimated to be strategic thinkers spend more time looking at competitor options than non-strategic thinkers. Chong, Camerer, and Ho (2005) show that higher type thinkers spend more time selecting an option in the game. Combined this evidence suggests that these econometric models of strategic thinking are validated in the laboratory: Players that are estimated to think strategically display other behavior that is consistent with this hypothesis.

3. Model and Empirical Strategy

In this section, we build on Camerer, Ho, and Chong (2004) to enable us to take the CH model to the ISP data. Our specification differs from the definitions used in laboratory experiments. In particular, in order to take the model to data outside the laboratory, we use observable data to allow ISPs to be heterogeneous in ways other than strategic thinking. Augereau, Greenstein, and Rysman (2006) show that ISP- and market-specific characteristics influence whether to adopt 56K modem technology at all and, if so, which technology to adopt. We therefore add the ISP- and market-level covariates used in that paper. This means that, rather than choosing randomly, a type-0 player's choice is the one with the higher intrinsic value to that player, independent of competitor choices. Higher-level players also consider the intrinsic value of each choice in addition to competitor behavior. In what follows, we formalize this approach.

Suppose there are J ISPs, $j=1,...,J$ that operate in markets indexed by i. ISPs observe market-specific characteristics x_i and ISP-specific characteristics x_j. Also, each ISP has four choices: adopt neither technology, adopt technology A, adopt technology B, or adopt both.[7] We use $s_j=\{0, A, B, AB\}$ to denote this choice set. We normalize $E[\pi_{ij}^{o} \mid k]=0$.

In our model, $E[\pi_{ij}^{s} \mid k]$ will depend on the ISP's level of strategic thinking, in addition to market-level and ISP characteristics. As discussed above, we assume a type-0 ISP (denoted by j) does not take competitor actions into account. Its expected profit in market i is therefore only a function of ISP- and market-level characteristics.

$$(1) \qquad E[\pi_{ij}^{A} \mid 0]=\beta_0^A + x_i\beta_1^A + x_j\beta_2^A$$

$$E[\pi_{ij}^{B} \mid 0]=\beta_0^B + x_i\beta_1^B + x_j\beta_2^B$$

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[7] For model generalizability and expositional simplicity, in this section we refer to Rockwell Semiconductor's K56Flex modem as technology A and US Robotics' X2 modem as technology B.

Here x_i are market-level characteristics that affect the profitability of adoption and x_j are ISP characteristics. For a type-k>0 ISP, its expected profit in market i is:

(2)
$$E[\pi_{ij}^A \mid k] = \beta_0^A + x_i\beta_1^A + x_j\beta_2^A + E[\psi_1^A(n_i^A+1) + \psi_2^A n_i^B + \psi_3^A n_i^{AB} \Big| X, \theta, k]$$ [8]

$$E[\pi_{ij}^B \mid k] = \beta_0^B + x_i\beta_1^B + x_j\beta_2^B + E[\psi_1^B n_i^A + \psi_2^B(n_i^B+1) + \psi_3^B n_i^{AB} \Big| X, \theta, k]$$

Here n_i^A, n_i^B, and n_i^{AB} are the (expected) number of market i competitors who adopt technologies A, B, and both, respectively. These will therefore be a function of the market and competitor characteristics. Then ψ represents coefficients on expected competitor behavior and β represents coefficients on other parameters of the profit function. For type-1 ISPs, the values for n_i^A, n_i^B, and n_i^{AB} are calculated assuming that all of their competitors are type-0 ISPs who choose the technology that maximizes their profits. For type-2 ISPs, these values are calculated assuming all of their competitors are either type-0 or type-1. For type-k ISPs, these values are calculated assuming all of their competitors are distributed between type-0 and type-(k-1). In this way we assume that all ISP- and market-specific characteristics are public information. Thus, any ISP can observe the characteristics of all the other ISPs and predict their behavior according to the distribution of types. Given ISP and market characteristics and the parameters of the model, the choices of type-0 ISPs are perfectly predictable up to the idiosyncratic error in the profit function. The choices of higher-level ISPs are consequently also iteratively known given the distribution of types.[9] Our modeling approach to study this type-dependent choice problem is similar to those that examine state-dependent choice problems.[10] Here we have type distributions

[8] We also estimate a symmetric specification where we restrict the values of β to be the same across technologies.
[9] Given that there are just four possible choices, this limits the number of levels that are identified separately from the error term.
[10] For example, state-dependent choice problems are part of the hidden Markov model in Netzer, Lattin, and Srinivasan (2008).

and type-dependent choice probabilities, while those methods have similar state distributions and state-dependent choice probabilities.

Following Camerer, Ho, and Chong (2004), we assume this distribution to be a truncated Poisson. In particular, we assume that types are distributed Poisson with parameter τ. The Poisson distribution is convenient because a single parameter describes it. As τ increases, the distribution of player types becomes relatively more strategic. We can assume that a type-k ISP believes its competitors are distributed truncated Poisson (at k-1) with the same parameter τ. Alternatively, in order to estimate how strategic ability varies with market and ISP characteristics, we modify this distribution to allow the Poisson parameter to vary with these characteristics. In particular, we set $\ln(\tau^j) = \gamma_0 + \gamma_1 z_{ij}$ where z includes three market-level characteristics (including the number of competitors in the market, the percentage of the population that lives in an urban area, and the percentage of the population that has graduated college) and a firm-level characteristic (number of markets served).[11]

Given its type, ISP j picks the choice that maximizes its profit: $\text{Max}_{s_j}\{0, \pi_j^A, \pi_j^B, \pi_j^{AB}\}$ Since ISPs operate in many markets and they offer the same technology in all markets, we assume that they add up the profits across markets and choose the technology that gives the highest total profit. Then,

$$\pi_j^o = 0\,,$$

$$\pi_j^A = \sum_i E[\pi_{ij}^A \mid k] + v_j^A\,,$$

[11] We use these market-level covariates because we found them to be strongly significant in many specifications. While it may seem unintuitive to include market level characteristics, we believe it is an empirical question whether they matter. For example, Ho, Camerer, and Weigelt (1998) find that the number of competitors is related to strategic behavior in the lab. One firm-level covariate (number of markets served) is included because we felt it made sense intuitively even though it is not significant in many specifications. Unfortunately, the only other firm-level variable in the data is whether the ISP is connected to the Internet backbone. We do not find this to be related to strategic thinking; we also see no intuitive reason to include it.

$$\pi_j^B = \sum_i E[\pi_{ij}^B \mid k] + v_j^B,$$

(3)

$$\pi_j^{AB} = \sum_i E[\pi_{ij}^A \mid k] + \sum_i E[\pi_{ij}^B \mid k] + v_j^A + v_j^B + \Gamma$$

$$\begin{pmatrix} v_j^A \\ v_j^B \end{pmatrix} \sim N(0,\Sigma) \text{ and } \Sigma = \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}.$$

Γ represents the additional payoff of adopting both technologies beyond the sum of adopting each technology.[12] Here the error terms v_j are ISP-level shocks that affect the profitability of the different technologies that are observed by the ISPs but not by the econometrician.

We can now predict multi-market ISP *j*'s choice probabilities, conditional on its type. The general procedure is as follows: We first calculate every ISP's branch-level profits (or market-level profits). Then we add them up by ISP to get the ISP-level profits. Next we consider each ISP's aggregate profit maximization problem to determine its technology adoption decision. Then we map every ISP's decision to all its branches. We repeat this procedure to get every ISP's expectation about other ISPs' decisions, conditional on it being of each possible type. We calculate the ISP's choice probabilities assuming that the ISP is maximizing profits, conditional on it being of each type.

Formally, the first step is to calculate ISP *j*'s choice probabilities if it is of type-0 (with probability $p_k^0(j)$, suppose k is the highest type possible): $p_k^0(j) \to \Pr_j^0 \leftrightarrow s_j^0 \in \{0, A, B, AB\}$. Similarly, we calculate all the other ISPs' choice probabilities if they are type-0. Then we map s_j^0 into s_{ij}^0, $\Pr_j^0$ into $\Pr_{i,j}^0$, $i=j_1,...,j_B$, $j=1,2,\ldots,J$ (where J=2,233 in our data). Second, if ISP *j* is a

[12] Gentzkow (2006) noted that ρ and Γ are not separately identified in a setting like ours, so we normalize Γ to be 0 in our estimation.

type-1 ISP (with probability $p_k^1(j)$), based on its beliefs about other ISPs' types and branch level decisions ($\Pr_{i,j}^0$), we calculate *j*'s expected branch-level profits. Adding up these profits, we obtain *j*'s aggregate profit level and its choice probabilities from its profit-maximizing problem: $p_k^1(j) \to \Pr_j^1 \leftrightarrow s_j^1 \in \{0, A, B, AB\}$. We similarly calculate all the other ISPs' choice probabilities if they are type-1 ISPs, and then we map s_j^1 into s_{ij}^1, $\Pr_j^1$ into $\Pr_{i,j}^1$, $i=j_1,\ldots,j_B$, $j = 1, 2, \ldots, J$. We repeat this procedure until we get all ISPs' choice probabilities under all types.

Mathematically, a type-*k* ISP *j*'s expected number of competitors adopting the technologies in market *i* can be shown by the vector:

$$\{E_j(n_i^A \mid k), E_j(n_i^B \mid k), E_j(n_i^{AB} \mid k)\} =$$

$$\{\sum_{m=0}^{m=k-1}\sum_{l\neq j}[p_{k-1}^m(l)\times \Pr_{i,l}^m(A)], \sum_{m=0}^{m=k-1}\sum_{l\neq j}[p_{k-1}^m(l)\times \Pr_{i,l}^m(B)], \sum_{m=0}^{m=k-1}\sum_{l\neq j}[p_{k-1}^m(l)\times \Pr_{i,l}^m(AB)]\}. \quad (4)$$

Here, all type-k ISPs assume that any other ISP (denoted by *j*) is distributed according to a normalized Poisson distribution with one parameter τ^j, from type-0 ($p_{k-1}^0(j)$) to type $k-1$ ($p_{k-1}^{k-1}(j)$). Again, note here each *ISP* has an idiosyncratic Poisson distribution parameter τ^j, while in the original CH model, each group of lab subjects has one idiosyncratic Poisson distribution parameter τ. In other words, in the original CH paper, all subjects' types are drawn from the same Poisson distribution with one parameter τ; while here each multi-market ISP is drawn from a generalization of the Poisson distribution where the τ varies with the ISP's characteristics according to the coefficients on these characteristics.

Next, we can compute ISP *j*'s aggregate choice probabilities (weighted by $p_k^m(j)$) with respect to the choice set *{0, A, B, AB}:*

(5)
$$p_j(0)=\sum_{l=0,...k} p_k^l(j)\times \Pr_j^l(0)\,,\ I_j(0)=\begin{cases}1, \text{ if } s_j=0\\ 0, \text{ otherwise}\end{cases};$$

$$p_j(A)=\sum_{l=0,...k} p_k^l(j)\times \Pr_j^l(A)\,,\ I_j(A)=\begin{cases}1, \text{ if } s_j=A\\ 0, \text{ otherwise}\end{cases};$$

$$p_j(B)=\sum_{l=0,...k} p_k^l(j)\times \Pr_j^l(B)\,,\ I_j(B)=\begin{cases}1, \text{ if } s_j=B\\ 0, \text{ otherwise}\end{cases};$$

$$p_j(AB)=\sum_{l=0,...k} p_k^l(j)\times \Pr_j^l(AB)\,,\ I_j(AB)=\begin{cases}1, \text{ if } s_j=AB\\ 0, \text{ otherwise}\end{cases}.$$

This gives the likelihood function:

(6)
$$\prod_j[(p_j(0))^{I_j(0)}(p_j(A))^{I_j(A)}(p_j(B))^{I_j(B)}(p_j(AB))^{I_j(AB)}].$$

We estimate this likelihood function using a genetic "differential evolution" algorithm (Storn and Price 1997). This method is simple and efficient for global optimization over continuous spaces. We combine this with a GHK simulator using 50 draws in order to simulate the choice probabilities (we choose this number based on Monte Carlo evidence in Keane (1994) and elsewhere). [13]

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[13] In the main results, we treat all ISPs' technology adoption decisions as simultaneous regardless of whether they first occur in July or October 1997. As Augereau, Greenstein, and Rysman (2006) discuss, the descriptive statistics suggest this is a reasonable thing to do. For example, in Table 1b, over four times as many ISPs had adopted Rockwell Semiconductor's technology in October as compared to July. In a robustness specification, we treat the decisions made before July as exogenous. So, if an ISP had adopted one technology by July, this ISP only needed to consider whether to adopt the other technology or not in October. Of course, for those ISPs that had adopted both technologies by July, they had no technology adoption choice to make in October. Our previous structure is still applicable to those ISPs that had adopted neither technology by July. It is possible that earlier decisions by ISPs were observed by later adopters. In order to reflect the influence of these potentially observed decisions in July, we incorporate them into the expectation formation process of all ISPs and update their profit functions and choice probabilities accordingly. For example, if type k ISP j adopted technology A by July, its choice probabilities in October conditional on its type are:
$$\{\Pr(s_j=0|k),\Pr(s_j=A|k),\Pr(s_j=B|k),\Pr(s_j=AB|k)\}=\{0,\Pr(\pi_j^{AB}<\pi_j^{A}|k),0,1-\Pr(\pi_j^{AB}<\pi_j^{A}|k)\}$$
where $\Pr(\pi_j^{AB}<\pi_j^{A}|k)=\Pr(\sum_i E[\pi_{ij}^{B}|k]+v_j^{B}+\Gamma<0)=\Phi(-\sum_i E[\pi_{ij}^{B}|k]-\Gamma)$.

Intuition for Identification

Our model is identified because the model predicts that different types will behave differently in otherwise identical situations. It relies on the assumption that we can assess the attractiveness of adopting the technologies to each ISP. For example, suppose we observe a market with three ISPs and we know that the optimal number of adopters is two. If we observe three adopt, then we can assume that they are all type-0. If we observe none adopt, then they must all be type-1 (and expect that their competitors both adopted as type-0s). The model will generate decision rules like this and we will compare these predictions to data. Each τ will generate a distribution of types. For example, if τ=1, 37% of players will be type-1 and less than 1% will be type-5. In contrast, if τ=3, 16% of players will be type-1 and 11% of players will be type-5. Given that we have a large number of ISPs (2,233) serving an even larger number of markets (9,070), we can find the value for τ that best fits the data to distribution of types predicted by the model.

4. Results

4.1 Model estimates

In this section, we discuss the parameter estimates. Table 2 presents the main results. Table 2 column 1 uses four different characteristics of the ISPs and the markets they serve to define τ. The results suggest that firms that operated in areas with more educated populations, that faced more competitors, and that operated in urban areas had higher values of τ.[14] In other words, the strategic thinking distributions for these types of firms first order stochastically dominate the distributions for other types of firms. Firms with these characteristics are therefore

[14] In this specification, operating in more markets is significantly and negatively associated with strategic thinking level; however, in our robustness checks in the online appendix the coefficient is often not significant and we therefore do not emphasize it.

more likely to be higher-type players and thus behave more strategically. These results are consistent with prior laboratory research. For example, Ho, Camerer, and Weigelt (1998) find that strategic thinking increases as the number of competitors increases and Chong, Camerer, and Ho (2005) find that laboratory subjects who attend a higher-quality school are more strategic.

Column 2 estimates the model where we assume τ to be equal across all ISPs. The estimated τ is 2.67 (i.e., exp(0.9809)). This value means that the number of type-0, type-1, type-2, type-3, type-4, and type-5 and above are 164, 437, 583, 519, 346, and 185, respectively. This is at the high end of the range of values for τ found in Camerer, Ho, and Chong (2004). For example, the median value from all of the experiments they examine is 1.6 and the maximum is 4.9. For a group of portfolio managers, τ is 2.8. We view this as providing external validity for the CH model: given that this is a business decision, we expect managers to think it through more carefully than undergraduates would in a lab. Still, the level of strategic thinking is still well within the range of the lab, suggesting that the laboratory insights do apply in our setting.

Rows 6, 7, 9, and 10 of table 2 show that ISPs typically differentiate from their rivals. The parameter ψ is negative when estimating a firm's incentives to adopt the same modem technology as its competitors and positive when estimating incentives to adopt a different technology. For example, rows 6 and 7 show that if an ISP adopted the K56Flex, then, all else equal, its competitor was more likely either to have adopted the X2 or to not have adopted at all. Furthermore, we find that the incentives *not to adopt* the same technology as a competitor were larger than the incentives *to adopt* the competing technology. This suggests that strategic thinking may have led to an overall decrease in adoption of 56K modems. We examine this idea in detail in section 4.4.

We explore robustness to a number of alternative specifications in the online appendix.[15] These results generally confirm our main findings.

4.2 Comparison to Augureau, Greenstein, and Rysman (2006)

Our results are consistent with Augereau, Greenstein, and Rysman (2006) although a comparison provides important additional insights into the consequences of allowing heterogeneity in strategic ability. Their objective was to determine whether ISPs coordinate to take advantage of potential network externalities or differentiate to generate local market power. As in our estimation, they allow for both coordination and differentiation to arise in their analysis. The key difference between our paper and theirs is that our paper allows for heterogeneity in managerial ability. Their primary contribution and main result is that ISPs tended to differentiate from their rivals when choosing which 56K modem technology to adopt. This is consistent with our results on ψ in rows 6, 7, 9, and 10 of table 2. Our primary empirical contribution instead arises from the estimates of the strategic ability parameter τ and the simulations of the consequences of varying strategic ability. Our model therefore provides additional and distinct insights because we can assess how ability affects outcomes.

A direct comparison of our results with Augereau, Greenstein, and Rysman provides an interesting further insight: Our estimated level of differentiation is much stronger (in significance and relative coefficient magnitude) than the one estimated in their paper. Given the assumptions of the CH model, this is expected: Low-type ISPs may not differentiate effectively. These would

[15] The robustness checks in the online appendix include (i) results using different maximum number of steps calculated, (ii) results for symmetric specifications where the incentives to adopt the technologies are identical except through strategic thinking, (iii) results where July decisions are treated as exogenous, (iv) results where each market is estimated independent of other markets (including specifications with random coefficients for market-specific unobserved heterogeneity), and (v) results where ISPs can only “better respond” rather than best respond (i.e. they respond as they plan to with probability 0.85 in one specification and 0.97 in the other).

be averaged with the others had we estimated a Perfect Bayesian Equilibrium model. In the CH equilibrium that we estimate, the coefficients are driven only by the firms that behave strategically.

It is important to note that the CH model does *not* generally fit the data better than the Perfect Bayesian Equilibrium model used in Augereau, Greenstein, and Rysman (2006). In particular, for most of the models the average log likelihoods in our estimates are similar to theirs. There is one interesting exception: our model fits the data better than theirs when we treat the July 1997 decisions as exogenous (online appendix table 2 column 4). We believe this is because these decisions are more likely to be truly simultaneous due to the short time horizon. In particular, suppose early adoption decisions (say, those in April) are observable by late adopters (say, those in October). Then the ISPs making a decision in October will be able to best-respond to the early adopters. This will mean that the resulting adoption patterns will more closely resemble Nash. In contrast, since it takes time to set up the technology, it is unlikely that late adopters (those in October) will be able to best-respond to ISPs that adopted in August. It is therefore more likely that conjectures about competitor behavior over a short time horizon will rely on k-step thinking. In this way, treating the July decisions as exogenous and observed, and then modeling only the subsequent decisions as simultaneous, is closer to the simultaneous game that we model. Therefore, this is suggestive of the usefulness of the CH model over the Nash model when the game is truly simultaneous.

4.3 Did high τ firms do better?

In this sub-section, we provide a test of the external validity of our estimates. We cannot explicitly test our model against the Nash equilibrium. Instead, we examine whether the ISPs that survived until April 2007 had a higher estimated value of τ. If the firms that are estimated to be more strategic are more likely to survive, we believe this provides some surface validity for our strategic ability parameter.[16]

Our data contain the URLs of 2,233 different ISPs that were operating in 1997. We manually visited each of these 2,233 URLs again in April 2007. Of the 2,233 URLs, 1,107 were still operating as ISPs that provided dial-up Internet, DSL, or both. Another 933 were no longer operating as ISPs. The remaining 193 were operating as ISPs but the visitor was forwarded to another website.[17]

We use this information in table 3a to assess the correlation between the strategic ability parameter (τ) predicted from our model and survival through 2007. All three columns show the same substantive result: those ISPs that survived (through continued operations or acquisition) have a higher value of τ. We use table 2 column 1 to predict τ, though results are robust to using the estimation in the online appendix to predict τ. Column 1 defines survival as either still operating as an ISP or having been acquired. Column 2 takes the ISPs that were acquired out of the data. Column 3 treats acquired ISPs as having exited.

Overall, table 3a shows that higher τ firms did better in that they were more likely to have survived for 10 years. We do not mean to say that the 56K modem decision itself led to survival. Instead, we argue that high strategic ability overall is likely correlated with observed strategic behavior in the decision to adopt 56K modems.[18] Firms that survived had higher

[16] Haile, Hortacsu, and Kosenok (2008) suggest this type of validation strategy in their paper on the difficulties in estimating Quantal Response Equilibria using data from outside the laboratory. They show that many strategies for estimating Perfect Bayesian Equilibria (including Seim 2006 and Augereau, Greenstein, and Rysman 2006) are equivalent to estimating Quantal Response Equilibria.

[17] For example, typing “www.abts.net” forwards the visitor to “www.earthlink.net.” We interpret this as the ISP having been acquired but show robustness to not including these ISPs.

[18] Stranger and Greenstein (2007) discuss a number of other strategic product and technology choices faced by ISPs and the relationship between these choices and the prices that ISPs charged.

estimated levels of strategic thinking in this context, and therefore we argue that they likely had higher levels of strategic thinking overall. This correlation between survival and strategic ability, however, needs to be treated as suggestive rather than conclusive evidence in favor of our model. It is possible that those variables correlated with estimated strategic thinking, τ, are correlated with survival for reasons independent of strategic thinking. Section 5 describes some limitations of the model in more detail.

Underlying this test is the assumption that strategic thinkers are more likely to be profitable and hence more likely to survive. While Stahl (1993) showed in an evolutionary setting that some non-strategic thinkers survive if they are lucky enough to randomly choose a good strategy, we find that strategic thinkers (i.e. those with higher estimated τ) do earn a higher profit on average in our model. In particular, table 3b shows that predicted profits and the predicted strategic ability parameter τ are strongly and positively correlated within the model. The purpose of this table is simply to show that, in our model, ISPs with higher τ generally earn higher profits: strategic thinkers *are* more likely to be profitable. Therefore, the result that strategic thinkers survive beyond the estimation period does provide external validity for our assertion that τ measures strategic thinking.

4.4 Consequences of Strategic Thinking on 56K Modem Diffusion

We next examine how different levels of strategic thinking may lead to different outcomes. Based on the coefficients of table 2 column 1, figures 1a and 1b show simulation results where we allow the distribution of strategic thinking to vary.[19] Figure 1a shows that the percentage of ISPs that provide at least one 56K modem technology falls as strategic thinking

[19] The qualitative results of this section do not change if we instead use the alternative specifications in the online appendix to generate the simulated values. The numbers in figure 1 are shown in table form in the online appendix.

rises. If everyone is a type-0 player, distribution of one or the other technology is over 99%. However, distribution falls under 50% as τ approaches two and it falls under 25% as τ approaches 5.[20] Thus figure 1a suggests that strategic thinking slows the overall diffusion of the technology: if the ISPs are more strategic then fewer will offer the upgraded service to their customers. Figure 1b adds two further insights: (1) fewer ISPs will adopt both technologies as strategic thinking rises and (2) the relative shares of the competitors will level off as strategic thinking rises. These results reflect the incentive to differentiate. When firms consider the competition, the model suggests that they understand that providing a different service from the competition increases profitability.

Besides the results in figure 1, we conducted a simulation where all players are type-1. Under this situation, less than 1% adopt both technologies and over 95% adopt US Robotics' technology, apparently in an attempt to differentiate from their expected type-0 competition. This simulation shows the importance of *heterogeneity* in strategic ability in providing interesting and reasonable insights. It is not simply bounded rationality: If everyone is boundedly rational in the same way but no structure is imposed in terms of reasonable beliefs, then the market outcomes become unbalanced.

In summary, the simulation results suggest that allowing for heterogeneity in strategic ability helps understand variation in ISP technology choices. Competitive considerations slowed the diffusion of 56K modem technology; however, diffusion would have been even slower if the ISPs were more strategic (as might be expected as the industry matures).

[20] Beyond $\tau = 5$, the effect of increasing τ appears to have little systematic impact on behavior. This may be due to our assumption (made for computational reasons) that ISPs are at most type-5 thinkers or it may be due to the fact that in an entry-type game, the number of choices available to the players is not large.

5. Limitations

As in any empirical work, this paper has a number of limitations. First, we assume, rather than test, the CH model. While we provide some evidence of external validity, our model does not nest Nash equilibrium assumptions. Our goal has been to understand the drivers of changes in the ability distribution parameter τ, assuming that the model behind it is correct. We rely on the prior experimental literature to support our modeling assumptions. Based on this literature, we measure strategic ability as the number of thinking steps a firm goes through in order to differentiate from its rivals. Therefore, two firms with different characteristics behave differently in the model in the *probabilistic* sense. We have to acknowledge that it is possible that the observed variation in managerial ability is simply variation in unobserved heterogeneity along other dimensions. Additionally, while we find that ISPs with high estimated τ were more likely to survive (despite being less likely to adopt 56K modems) and that the results on what drives the strategic ability parameter are intuitive, without a clear instrument that is correlated with τ but not survival, this evidence remains suggestive. ISPs with more competitors that operate in educated urban markets are more likely to be strategic. Still, we can put forth alternative explanations for our intuitive results and the correlation between having a high estimated τ and surviving. Thus, we cannot say that the CH model is somehow “better” than assuming Nash behavior. In fact, our model does not consistently fit the data better than Augereau, Greenstein, and Rysman’s Nash equilibrium model. Instead, we argue that the assumptions of the CH model allow us to learn different things from the data than a Nash model allows.

Second, a somewhat restrictive assumption inherent in the CH theory is that all players think they are smarter than all other players. In other words, the CH theory precludes the possibility that players expect their competitors to be their equals in level of strategic thinking.

However, if we allow players to think rivals may have equal ability, then this will result in a mutually best response through infinitely many iterations, meaning the uniqueness of the solution would be lost.

Third, we do not have rich data on managerial characteristics. While we found several market-level characteristics to be related to our measure of strategic ability, we cannot say much about the manager-specific factors that are related to ability. More information on managers would allow for a deeper understanding of the types of managers that are more strategic.

Fourth, we identify a very specific kind of ability: the ability to correctly conjecture competitor behavior. We cannot say anything about the ability of managers in other dimensions that are relevant to success.

Finally, the empirical setting may differ from the model in ways that may affect the results in unforeseen ways. For example, multi-market ISPs may weight markets differently than our assumptions suggest. ISPs may be forward-looking firms that consider future market changes that we cannot measure. There may be unobservable shocks to adoption costs or benefits that affect technology choice. For example, a temporary, locally focused, price promotion for one technology may influence our results on strategic behavior. Furthermore, although adoption takes place over a short period of time, the game we study is not truly a simultaneous game. ISPs may respond to each other's decisions quickly. Finally, it is also possible that some ISPs are playing a coordination game rather than a differentiation game. While Augereau, Greenstein, and Rysman (2006) find that ISPs did not behave this way on average, if some ISPs were coordinating, they will appear in the estimates to be less strategic.

6. Conclusion

As the first study to our knowledge to combine behavioral game theory with the structural models of the New Empirical Industrial Organization, our paper provides a new framework for understanding variation in the decisions of managers who face similar choices. This framework allows us to show how strategic thinking affects outcomes.

We find that strategic thinking slowed the diffusion of 56K modem technology, supporting Reinganum's (1981) theoretical work on the subject. In particular, our results suggest that strategic thinking by some customers substantially reduced modem distribution for both Rockwell Semiconductor and US Robotics. This impact suggests that competitive considerations in technology adoption are important to managers of business-to-business products and for policymakers trying to encourage technology diffusion. That said, it is also important for both managers and policymakers to consider that variation exists in strategic thinking.

Our simulations suggest that adoption rates would have been much lower if the average level of strategic thinking were higher. Generally speaking, in industries with inexperienced managers, competitive considerations may be less important. This paper therefore builds on the rich existing literature that generally focuses on the diffusion of new consumer-oriented products (starting with Bass 1969).

Our results suggest two new variables that should be considered when a new product is aimed at businesses: (1) the strategic consequences of the product for the targeted industry and (2) the strategic ability of the players. The competitive considerations of business customers affect diffusion, and this is particularly important in industries with sophisticated, experienced managers. Consistent with the theoretical results in Soberman (2007), this means it may be most effective for business-to-business marketers to target just one firm in each market, as the marginal returns to targeting multiple competing customers will be lower. Furthermore, our results also suggest that incentives for business customers to differentiate from competitors may hinder the creation of winner-take-all markets.

We show in this paper that estimating heterogeneity in managerial types is feasible and provides interesting insights. Several opportunities for future work remain that builds structural econometrics models from the assumptions of behavioral games. We encourage future researchers to examine whether strategic thinking limits (or encourages) technology adoption in other industries and whether this impact increases as industries mature and managers become more experienced. Similarly, scholars could apply this modeling technique to data on entry (as suggested by Ho, Lim, and Camerer 2006) to explore how strategic thinking limits (or encourages) entry and how this differs across markets and over time.

References

Aradillas-Lopez, Andres, and Elie Tamer (2008), “The Identification Power of Equilibrium in Games,” forthcoming *Journal of Business and Economic Statistics.*

Ataman, Berk M., Carl Mela, and Harald J. van Heerde (2008), “Building Brands,” forthcoming *Marketing Science*.

Augereau, A., S. Greenstein and M. Rysman (2006), “Coordination vs. Differentiation in a Standards War: 56K Modems,” *RAND Journal of Economics,* 37(4), 887-909.

Bajari, Patrick, Han Hong, and Stephen Ryan (2004), “Identification and Estimation of Discrete Games of Complete Information,” NBER Working Paper #T0301.

Bass, Frank M (1969), “A New Product Growth for Model Consumer Durables,” *Management Science,* 15(5), 215-227.

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.

Brown, Alexander L., Colin F. Camerer, and Dan 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 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.

Chan, Tat Y., Barton H. Hamilton, and Christopher Makler (2007), “Using Expectations Data to Infer Managerial Objectives and Choices.” Working Paper, Washington University.

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.

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.

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

Costa-Gomes, Miguel, Vincent P. Crawford, and Bruno Broseta (2001), “Cognition and Behavior in Normal-Form Games: An Experimental Study,” *Econometrica*, 65(5), 1193-1235.

Gentzkow, Matthew A. (2007), “Valuing New Goods in a Model with Complementarity: Online Newspapers”, *American Economic Review, 97*(3), 713 - 44.

Greenstein, Shane (2000), “Building and Delivering the Virtual World: The Commercial Internet Access Market,” *Journal of Industrial Economics*, 48(4), 391-411.

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

Haruvy, E., D. Stahl, and P. Wilson (2001), "Modeling and testing for heterogeneity in observed strategic behavior," *Review of Economics and Statistics*, 83(1), 146-157.

Ho, Teck H., C. Camerer, and K. Weigelt (1998), “Iterated Dominance and Iterated Best-Response in *p*-Beauty Contests,” *American Economic Review*, 88, 947-969.

Ho, Teck H., Noah Lim, and Colin F. Camerer (2006), "Modeling the Psychology of Consumer and Firm Behavior with Behavioral Economics," *Journal of Marketing Research*, 43, 307-331.

Hortacsu, Ali, and Steven L. Puller (2007), "Understanding Strategic Bidding in Multi-Unit Auctions: A Case Study of the Texas Electricity Spot Market," forthcoming *RAND Journal of Economics*.

Keane, Michael (1994), "A Computationally Practical Simulation Estimator for Panel Data," *Econometrica*, 62(1): 95-116.

Lim, Noah, and Teck-Hua Ho (2007), "Designing Price Contracts for Boundedly Rational Customers: Does the Number of Blocks Matter?" *Marketing Science*, 26, 312-326.

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

Nagel, R. (1995), "Unraveling in Guessing Games: An Experimental Study," *American Economic Review*, 85, 1313-1326.

Netzer, O., J. Lattin, and V. Srinivasan (2008), "A Hidden Markov Model of Customer Relationship Dynamics," forthcoming *Marketing Science*.

Reinganum, Jennifer F. (1981), "Market Structure and the Diffusion of New Technology," *Bell Journal of Economics*, 12(2), 618-624.

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

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

Soberman, David A. (2007), "Marketing Agencies, Media Experts, and Sales Agents: Helping Competitive Firms Improve the Effectiveness of Marketing," Working Paper, INSEAD.

Stahl, Dale O. (1993), "Evolution of Smart$_n$ Players," *Games and Economic Behavior* 5(4), 604-617.

Stahl, Dale O. II and Paul W. Wilson (1994), "Experimental Evidence on Players' Models of Other Players," *Journal of Economic Behavior and Organization*, 25, 309-327.

Storn, Rainer and Kenneth Price (1997), "Differential Evolution – A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces," *Journal of Global Optimization*, 11, 341-359.

Stranger, Greg and Shane Greenstein (2007), "Pricing in the Shadow of Firm Turnover: ISPs during the 1990s," forthcoming *International Journal of Industrial Organization.*

Table 1a: Summary Statistics by Market (N=9070)

Variable	Mean	Std Dev.	Minimum	Maximum
# of ISPs in the market	23.8353	29.7951	1	139
# of backbone providers	6.5793	17.4011	0	106
% population urban	0.4612	0.3993	0	1
% population in different county 5 yrs ago	0.1704	0.0807	0	0.8667
Median household income	42644.3	14719.24	6136	200001
% population college graduate	0.0848	0.0515	0	0.825
# of business establishments/person	0.0235	0.00667	0.002772	0.09811

Table 1b: Summary Statistics by ISP (N=2233)

Variable	Mean	Std Dev.	Minimum	Maximum
Choose Rockwell (A) in October	0.2342	0.4236	0	1
Choose US Robotics (B) in October	0.1742	0.3794	0	1
Choose both in October	0.0828	0.2757	0	1
Choose neither in October	0.5087	0.5000	0	1
Choose Rockwell (A) in July	0.0502	0.2183	0	1
Choose US Robotics (B) in July	0.0828	0.2757	0	1
Choose both in July	0.0121	0.1093	0	1
Choose neither in July	0.8549	0.3523	0	1
# of markets served	96.814	451.880	1	4916
ISP has digital connection (T1 or ISDN)	0.7443	0.4364	0	1

Table 1c: Summary Statistics by Observation (N=216,186)

Variable	Mean	Std Dev.	Minimum	Maximum
Choose Rockwell (A) in October	0.1347	0.3414	0	1
Choose US Robotics (B) in October	0.1706	0.3762	0	1
Choose both in October	0.0905	0.2869	0	1
Choose neither in October	0.6042	0.4890	0	1
Choose Rockwell (A) in July	0.0149	0.1212	0	1
Choose US Robotics (B) in July	0.0449	0.2071	0	1
Choose both in July	0.00828	0.0906	0	1
Choose neither in July	0.9319	0.2519	0	1
# of ISPs in the market	61.0763	35.8317	1	139
# of backbone providers	22.1733	33.1896	0	106
ISP has digital connection (T1 or ISDN)	0.5981	0.4903	0	1
Missing	0.2873	0.4525	0	1
% population urban	0.6808	0.3793	0	1
% population in different county 5 yrs ago	0.1663	0.0850	0	0.8667
Median household income	50352.8	18249.4	6136	200001
% population college graduate	0.1068	0.0574	0	0.825
# of business establishments/person	0.0241	0.00605	0.002772	0.09811

Table 2: Main Results

			(1)	(2)
Correlates with strategic thinking parameter τ (γ)	1	Constant (γ_0)	0.6716** (0.0364)	0.9809** (0.0152)
	2	ln(# of markets served)	-0.0221** (0.0059)	
	3	ln(# ISPs in market)	0.0403** (0.0137)	
	4	% population urban	0.1569** (0.0481)	
	5	% population college graduate	1.1731** (0.2177)	
Competitive incentives for adopting Rockwell's K56Flex (ψ^A)	6	# of ISP's on Rockwell	-2.8343** (0.4297)	-3.1408** (0.4098)
	7	# of ISP's on US Robotics	1.0453** (0.1929)	2.1284** (0.3243)
	8	# of ISP's on both technologies	-2.3236** (0.4742)	-5.3661** (0.8573)
Competitive incentives for adopting US Robotics' X2 (ψ^B)	9	# of ISP's on Rockwell	0.2653** (0.0927)	0.3086** (0.0422)
	10	# of ISP's on US Robotics	-1.0847** (0.1809)	-0.8824** (0.0699)
	11	# of ISP's on both technologies	1.7539** (0.28)	1.2991** (0.1593)
Controls: Non-strategic factors that affect adopting Rockwell's K56Flex (β^A)	12	Constant	-1.8913* (0.7786)	-2.381** (0.0773)
	13	ln(# ISPs in market)	0.3648** (0.0737)	-0.1112** (0.0205)
	14	ISP has digital connection	2.3463** (0.3541)	2.5445** (0.3696)
	15	missing	-0.6874** (0.1592)	-0.0368** (0.01)
	16	ln(median household income)	0.211** (0.0801)	0.2575** (0.007)
	17	# of business establishments per person	3.2702* (1.6001)	3.005* (1.2269)
	18	% population college graduate	-2.1197* (0.8621)	-3.3205** (0.3541)
	19	% population urban	0.2318 (0.1916)	0.2919** (0.083)
	20	% county population in different county 5 yrs ago	-0.0557 (0.5879)	1.1854** (0.2251)
	21	# of backbone providers	-0.0428** (0.0064)	-0.0017* (0.0008)
Controls: Non-strategic factors that affect adopting US Robotics' X2 (β^B)	22	Constant	-6.3662** (0.5978)	-3.2724** (0.0186)
	23	ln(# ISPs in market)	0.0042 (0.0154)	0.0661** (0.0068)
	24	ISP has digital connection	1.0491** (0.1892)	0.9094** (0.0754)
	25	missing	0.0207 (0.0272)	-0.0002 (0.001)
	26	ln(median household income)	0.5909** (0.0567)	0.2964** (0.0028)
	27	# of business establishments per person	-4.2215+ (2.4711)	-0.9406 (0.5672)
	28	% population college graduate	2.2869** (0.6438)	1.3414** (0.3461)
	29	% population urban	-0.4507** (0.1212)	-0.1257** (0.0274)
	30	% county population in different county 5 yrs ago	0.1165 (0.3937)	-0.1849 (0.1407)
	31	# of backbone providers	0.0276** (0.0078)	-0.0111** (0.0009)
	32	ρ	-0.1765 (0.271)	0.0617 (0.2527)
	33	log likelihood	-2623.0	-2644.8

+significant at 90% confidence level. *significant at 95% confidence level. **significant at 99% confidence level.

Table 3a: ISPs with higher τ are more likely to have survived to April 2007

	(1)	(2)	(3)
	All ISPs (τ defined as in table 2, column 3)	Only ISPs that maintain an independent website	Acquired ISPs treated as having exited
τ	0.2259* (0.0915)	0.2247* (0.0941)	0.1943* (0.0907)
constant	-0.3848 (0.2413)	-0.4819+ (0.2481)	-0.5203* (0.2394)
log likelihood	-1514.4	-1403.7	-1545.4
N	2233	2040	2233

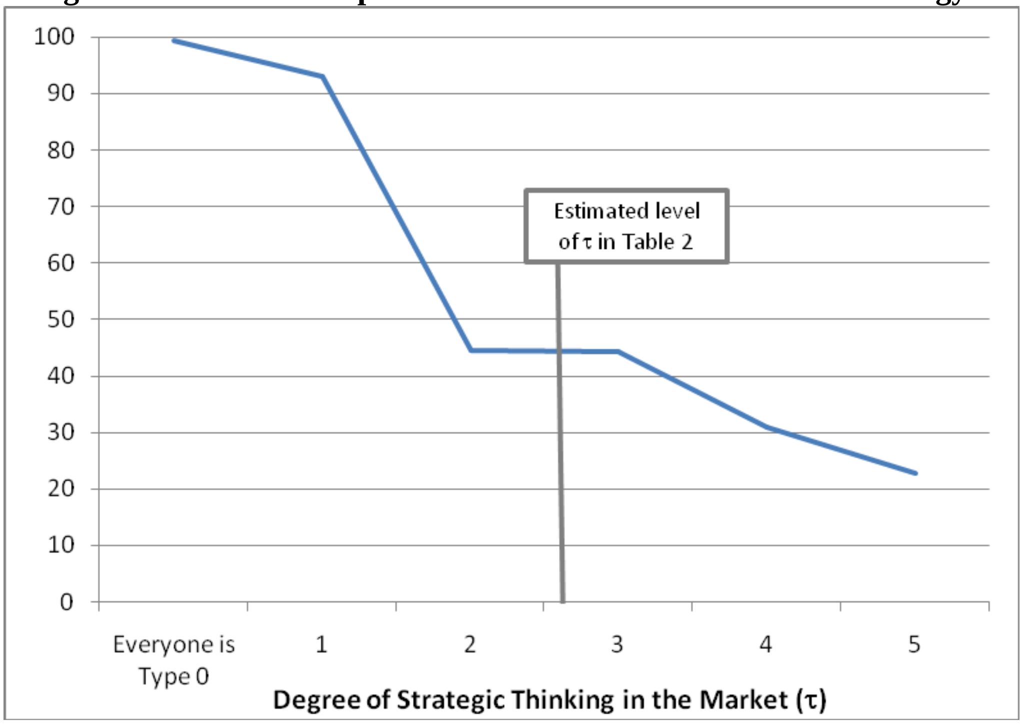
Probit regression of survival on predicted τ
+significant at 90% confidence level. *significant at 95% confidence level.

Table 3b: The model predicts ISPs with higher τ will have higher profits

	(1)	(2)
	All ISPs (τ defined as in table 2, column 3)	Only ISPs that maintain an independent website
τ	0.4671** (0.0919)	0.4605** (0.0939)
constant	-0.8348** (0.2425)	-0.8283** (0.2479)
R-squared	0.0115	0.0117
N	2233	2040

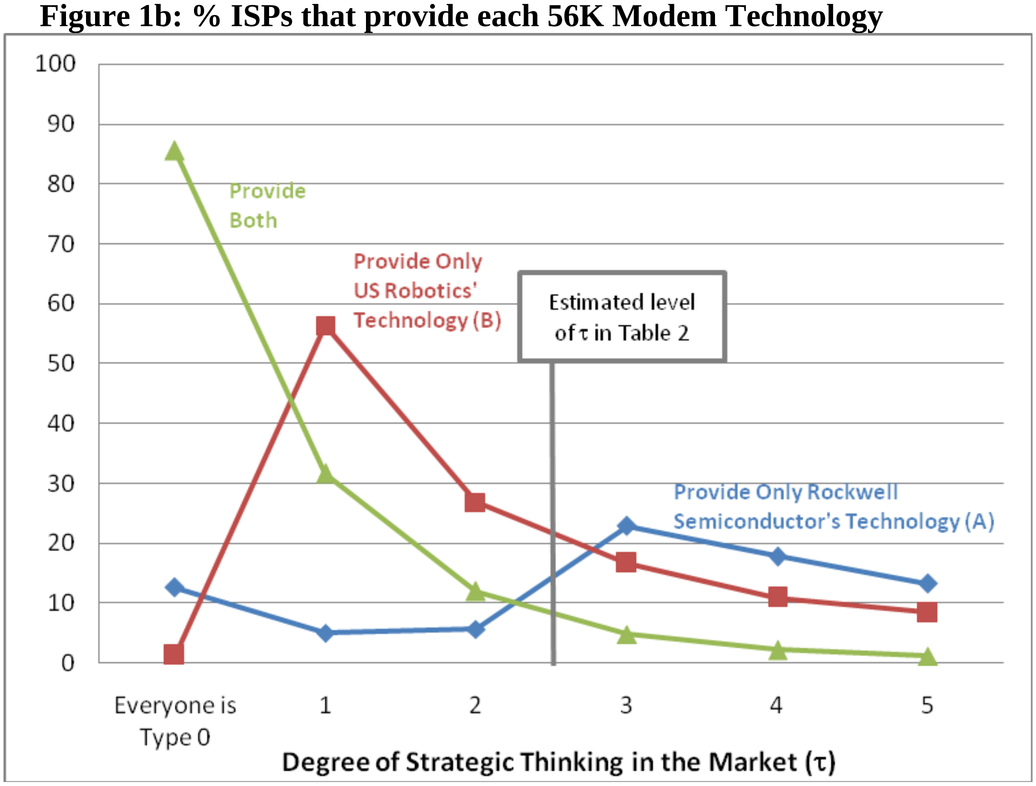
OLS regression of predicted profits on predicted τ
*significant at 99% confidence level.

Figure 1a: % ISPs that provide at least one 56K Modem Technology



Simulations based on table 2 column 2. A table showing the numbers that generated this figure is available in the online appendix.

Figure 1b: % ISPs that provide each 56K Modem Technology



Simulations based on table 2 column 2. A table showing the numbers that generated this figure is available in the online appendix.

Appendix Table 1: Levels of Thinking (# of types allowed in estimation)[a]

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Up to Type-0	Up to Type-1	Up to Type-2	Up to Type-3	Up to Type-4	Up to Type-5	Up to Type-6
Correlates with strategic thinking parameter τ (γ)	Constant (γ_0)		0.2462** (0.0280)	0.3947** (0.00135)	0.6886** (0.00334)	0.7144** (0.0489)	0.5679** (0.0494)	0.5549** (0.0135)
	ln(# of markets served)		-0.1864** (0.00822)	-0.3867** (0.00155)	0.00575 (0.00509)	-0.0175 (0.0129)	0.000563 (0.00369)	0.000687 (0.00301)
	ln(# ISPs in market)		0.0238 (0.0165)	0.0933** (0.000516)	0.0407** (0.00739)	0.0445** (0.0146)	0.0403** (0.0138)	0.0303** (0.00366)
	% population urban		1.2013** (0.0477)	0.5658** (0.00196)	0.3577** (0.00618)	0.3280** (0.0342)	0.2701** (0.0431)	0.2649** (0.0211)
	% population college graduate		-6.1273** (0.00925)	-4.6629** (0.000861)	0.8968** (0.00772)	-0.5735** (0.0901)	0.3950* (0.1683)	0.5982** (0.0490)
Competitive incentives for adopting Rockwell's K56Flex (ψ^A)	# of ISP's on Rockwell		-0.0416** (0.00851)	-0.0550** (0.00160)	-4.7685** (0.00989)	-3.9492** (0.0945)	-5.6544** (0.3094)	-9.3099** (0.1579)
	# of ISP's on US Robotics		0.0376** (0.00872)	0.0623** (0.00255)	0.1370** (0.000872)	0.1077** (0.00300)	0.5900** (0.0568)	1.0175** (0.0428)
	# of ISP's on both technologies		0.00354** (0.0000874)	-0.00915** (0.00118)	-0.0654** (0.000982)	0.0114** (0.000552)	-1.0862** (0.14407)	-1.8378** (0.1011)
Competitive incentives for adopting US Robotics' X2 (ψ^B)	# of ISP's on Rockwell		1.4720** (0.00821)	1.1988** (0.00596)	1.8447** (0.0244)	1.4388* (0.5700)	2.4819** (0.3872)	4.2772** (0.2901)
	# of ISP's on US Robotics		-1.4038** (0.00794)	-1.6029** (0.00617)	-4.6372** (0.0299)	-3.9966** (0.0885)	-5.6658** (0.3085)	-9.2913** (0.1752)
	# of ISP's on both technologies		-0.0156** (0.000362)	0.5645** (0.00396)	5.5753** (0.0485)	2.9390** (0.1348)	5.9635** (0.3824)	9.6295** (0.2692)
Controls: Non-strategic factors that affect adoption (β)	Constant	0.00662** (0.000776)	-0.1642** (0.00000365)	-0.1660** (0.00000831)	-0.0874** (0.0000602)	-0.0671** (0.00493)	-0.2487** (0.00885)	-0.0483** (0.00805)
	ln(# ISPs in market)	0.00117** (0.000199)	0.000137** (0.00000135)	-0.000223** (0.00000279)	0.0231** (0.0000204)	0.00277+ (0.00166)	0.0114** (0.00309)	0.0113** (0.00213)
	ISP has digital connection	0.000144 (0.000161)	0.000273** (0.0000106)	0.000133** (0.0000174)	4.6722** (0.00905)	3.8302** (0.0925)	5.5712** (0.3059)	9.1887** (0.1640)
	missing	0.000121 (0.000179)	-0.000102 (0.0000199)	-0.0000805 (0.000103)	-0.000315** (0.0000237)	0.000713** (0.000183)	0.0118** (0.00310)	0.0108** (0.00203)
	ln(median household income)	0.00152** (0.0000538)	0.0173** (0.00000266)	0.0175** (0.0000366)	0.00620** (0.00000470)	0.0118** (0.0000966)	0.0235** (0.00153)	0.00527** (0.000907)
	# of business establishmts per person	-0.6510** (0.00154)	-0.4192** (0.000592)	-0.1879** (0.000746)	0.3304** (0.00637)	-0.1679* (0.0768)	-1.1268** (0.2290)	-1.1982** (0.0789)
	% population college graduate	-0.0255** (0.000847)	-0.1448** (0.000351)	-0.1742** (0.0000321)	0.4244** (0.00455)	0.7111** (0.0242)	0.5563** (0.0967)	0.5177** (0.0653)
	% population urban	-0.00305** (0.000746)	0.00626** (0.0000795)	0.00719** (0.0000172)	-0.0118** (0.000866)	-0.0657** (0.00429)	-0.0340** (0.0102)	-0.0332** (0.00991)
	% county population in different county 5 yrs ago	-0.0430** (0.0000405)	-0.00884** (0.000528)	-0.0160** (0.000104)	-0.4005** (0.00138)	-0.4141** (0.0160)	-0.1865** (0.0663)	-0.2003** (0.0445)
	# of backbone providers	-0.0000339** (0.00000829)	-0.0000142** (0.000000509)	-0.0000359** (0.00000166)	-0.00291** (0.00000295)	-0.00192** (0.0000827)	-0.00128** (0.000169)	-0.00109** (0.0000879)
	log likelihood	-3034.6	-2744.7	-2735.4	-2712.3	-2664.7	-2644.7	-2641.8

[a]Assumes symmetry between factors that drive adoption of technology A and technology B (aside from differentiation).
+significant at 90% confidence level. *significant at 95% confidence level. **significant at 99% confidence level.

Appendix Table 2: Robustness to Alternative (Symmetric) Specifications

		(1)	(2)	(3)	(4)	(5) [a]
		Basic model	Determinants of τ not estimated	Allow correlation between A & B errors	July Decisions Treated as Exogenous	Single-market ISP model
Correlates with strategic thinking parameter τ (γ)	Constant (γ_0)	0.5679** (0.0494)	0.9000** (0.0150)	0.5874** (0.0543)	0.7479** (0.007)	0.5451** (0.0110)
	ln(# of markets served)	0.000563 (0.00369)		-0.00991 (0.00877)	-0.012* (0.0058)	N/A
	ln(# ISPs in market)	0.0403** (0.0138)		0.0409** (0.0147)	0.057** (0.0066)	0.1145** (0.00318)
	% population urban	0.2701** (0.0431)		0.2225** (0.0533)	0.1253** (0.0125)	-0.0287* (0.0144)
	% population college graduate	0.3950* (0.1683)		0.7488** (0.2849)	1.1289** (0.0127)	-0.0320** (0.00631)
Competitive incentives for adopting Rockwell's K56Flex (ψ^A)	# of ISP's on Rockwell	-5.6544** (0.3094)	-5.6572** (1.0501)	-5.6821** (0.0831)	-2.6209** (0.053)	-0.3796** (0.00532)
	# of ISP's on US Robotics	0.5899** (0.0568)	0.1551** (0.0288)	0.6133** (0.0527)	0.1652** (0.0093)	-0.00807** (0.000354)
	# of ISP's on both technologies	-1.0862** (0.1441)	0.00734** (0.00248)	-1.0773** (0.1515)	-0.152** (0.0268)	0.0113** (0.000241)
Competitive incentives for adopting US Robotics' X2 (ψ^B)	# of ISP's on Rockwell	2.4819** (0.3872)	2.6414** (0.9817)	2.5865** (0.2583)	-0.2315 (0.172)	0.2472** (0.0156)
	# of ISP's on US Robotics	-5.6658** (0.3085)	-5.7030** (1.0444)	-5.6954** (0.0739)	-2.5025** (0.0404)	-1.1694** (0.0199)
	# of ISP's on both technologies	5.9635** (0.3824)	3.9459** (0.7064)	5.9614** (0.0732)	0.8055** (0.083)	1.0465** (0.0252)
Controls: Non-strategic factors that affect adoption (β)	Constant	-0.2487** (0.00885)	-0.0522** (0.00204)	-0.2801** (0.0306)	0.0315* (0.0124)	0.0544** (0.0129)
	ln(# ISPs in market)	0.0114** (0.00309)	-0.00465** (0.000693)	0.0107** (0.00402)	-0.0011 (0.0033)	0.3754** (0.00252)
	ISP has digital connection	5.5712** (0.3059)	5.5266** (1.0403)	5.5933** (0.0719)	2.48** (0.0207)	-0.1928** (0.0135)
	missing	0.0118** (0.00310)	0.00177** (0.000163)	0.0114** (0.00363)	0.00001 (0.0002)	-2.1305** (0.0108)
	ln(median household income)	0.0235** (0.00153)	0.0192** (0.00128)	0.0265** (0.00258)	-0.0044** (0.0007)	-0.000561 (0.000653)
	# of business establishments per person	-1.1268** (0.2290)	-3.4383** (0.6078)	-0.5293 (0.4694)	-2.5307** (0.0102)	-0.00238 (0.00563)
	% population college graduate	0.5563** (0.0967)	1.0594** (0.1069)	0.5043** (0.155)	1.3298** (0.07)	0.00291 (0.00507)
	% population urban	-0.0340** (0.0102)	-0.0988** (0.00953)	-0.0359* (0.0144)	-0.0516** (0.0104)	-0.000445 (0.000872)
	% county population in different county 5 yrs ago	-0.1865** (0.0663)	-0.5118** (0.0417)	-0.2268* (0.1012)	0.026 (0.079)	-0.00169 (0.00421)
	# of backbone providers	-0.00128** (0.000169)	-0.000824** (0.0000394)	-0.00120** (0.000279)	-0.0017** (0.0004)	0.00203** (0.0000371)
	ρ			-0.4888** (0.0148)	-0.4825** (0.0103)	
	log likelihood	-2644.7	-2677.3	-2633.7	-2082.9	-225,705

+significant at 90% confidence level. *significant at 95% confidence level. **significant at 99% confidence level.

[a] The single market ISP model treats each local branch of a multi-market ISP as an independent decision-maker, which means that local branches of the same ISP make independent decisions and that these decisions can be different from each other. In the multi-market ISP model presented in Section 3, we have the constraint that all branches of a multi-market ISP must make the same choice.

Appendix Table 3: Better-Respond rather than best-respond

			(1)	(2)
			97% accuracy of what lower types should do	85% accuracy of what lower types should do
Correlates with strategic thinking parameter τ (γ)	1	Constant (γ_0)	0.6832** (0.0476)	0.7344** (0.042)
	2	ln(# of markets served)	-0.014** (0.0053)	-0.0338** (0.0035)
	3	ln(# ISPs in market)	0.0412* (0.0166)	0.0495** (0.013)
	4	% population urban	0.2029** (0.0673)	0.2542** (0.0441)
	5	% population college graduate	0.7775** (0.0818)	1.4826** (0.197)
Competitive incentives for adopting Rockwell's K56Flex (ψ^A)	6	# of ISP's on Rockwell	-3.2773** (0.175)	-3.5464** (0.3267)
	7	# of ISP's on US Robotics	1.1942** (0.079)	1.0159** (0.0865)
	8	# of ISP's on both technologies	-2.8131** (0.192)	-2.6232** (0.2287)
Competitive incentives for adopting US Robotics' X2 (ψ^B)	9	# of ISP's on Rockwell	0.2797** (0.0598)	0.5351** (0.0505)
	10	# of ISP's on US Robotics	-1.1876** (0.1787)	-3.9845** (0.3165)
	11	# of ISP's on both technologies	2.0056** (0.297)	8.8276** (0.7267)
Controls: Non-strategic factors that affect adopting Rockwell's K56Flex (β^A)	12	Constant	-2.136** (0.0047)	-4.9438** (0.2324)
	13	ln(# ISPs in market)	0.3817** (0.002)	0.7244** (0.0742)
	14	ISP has digital connection	2.8437** (0.1815)	3.2915** (0.3206)
	15	missing	-0.8048** (0.0092)	-1.0363** (0.1031)
	16	ln(median household income)	0.2292** (0.0021)	0.4797** (0.0246)
	17	# of business establishments per person	3.3227** (0.6973)	-15.0931** (4.1787)
	18	% population college graduate	-1.7764** (0.2589)	3.4961* (1.5167)
	19	% population urban	0.322** (0.0522)	0.6561* (0.2616)
	20	% county population in different county 5 yrs ago	-0.3869 (0.2872)	-0.6729 (0.5935)
	21	# of backbone providers	-0.0414** (0.0003)	-0.0728** (0.007)
Controls: Non-strategic factors that affect adopting US Robotics' X2 (β^B)	22	Constant	-8.8489** (0.1782)	-19.8065** (2.0141)
	23	ln(# ISPs in market)	0.0249 (0.0195)	-0.0173+ (0.0091)
	24	ISP has digital connection	1.1319** (0.167)	3.6686** (0.2961)
	25	missing	0.0215 (0.0301)	0.2385** (0.0212)
	26	ln(median household income)	0.8171** (0.0154)	1.8279** (0.19)
	27	# of business establishments per person	0.3058 (0.5631)	4.6567* (2.3319)
	28	% population college graduate	1.2688** (0.1553)	2.3056** (0.5884)
	29	% population urban	-0.5674** (0.0985)	-0.2524+ (0.1403)
	30	% county population in different county 5 yrs ago	0.3201** (0.1171)	-0.8019** (0.1086)
	31	# of backbone providers	0.0343** (0.0042)	0.0499** (0.0062)
	32	ρ	-0.2177 (0.3388)	-0.2329 (0.5547)
	33	log likelihood	-2617.3	-2601.7

+significant at 90% confidence level. *significant at 95% confidence level. **significant at 99% confidence level.

Appendix Table 4:
Robustness to (Symmetric, Single Market) Specifications with Unobserved Heterogeneity

			(1)[a]	(2)[a]	(3)[a]	(4)[a]
			500 markets, with heterogeneity	500 markets, no heterogeneity	1000 markets, with heterogeneity	1000 markets, no heterogeneity
Correlates with strategic thinking parameter τ (γ)	1	Constant (γ_0)	0.3273** (0.0997)	0.3259** (0.0932)	0.3760** (0.0954)	0.3757* (0.1778)
	2	ln(# of markets served)	N/A	N/A	N/A	N/A
	3	ln(# ISPs in market)	0.1699** (0.0288)	0.1705** (0.0262)	0.1499** (0.0295)	0.1499** (0.046)
	4	% population urban	0.0704 (0.0529)	0.0692 (0.0513)	-0.0561 (0.0394)	-0.0561 (0.0417)
	5	% population college graduate	-0.1191 (0.3224)	-0.1225 (0.3059)	-0.2411 (0.5678)	-0.2407 (0.3442)
Competitive incentives for adopting Rockwell's K56Flex (ψ^A)	6	# of ISP's on Rockwell	-0.8652** (0.0543)	-0.844** (0.0644)	-0.7219** (0.1433)	-0.7222** (0.1305)
	7	# of ISP's on US Robotics	-0.0371** (0.0068)	-0.0378** (0.0062)	-0.3609+ (0.2082)	-0.361+ (0.1934)
	8	# of ISP's on both technologies	0.1448** (0.0076)	0.1389** (0.0154)	0.58** (0.2245)	0.5801** (0.1771)
Competitive incentives for adopting US Robotics' X2 (ψ^B)	9	# of ISP's on Rockwell	0.053 (0.1942)	0.1371 (0.2026)	0.9428** (0.0357)	0.9435** (0.0282)
	10	# of ISP's on US Robotics	-1.9824** (0.3237)	-1.9904** (0.2161)	-0.8353** (0.0312)	-0.8361** (0.0227)
	11	# of ISP's on both technologies	2.4442** (0.5052)	2.5732** (0.3565)	-0.1263** (0.0228)	-0.1262** (0.014)
Controls: Non-strategic factors that affect adoption (β)	12	Constant (β_0)	0.6289** (0.0796)	0.5269 (0.3863)	-0.1822** (0.0633)	-0.1815** (0.0302)
	13	ln(# ISPs in market)	0.3012** (0.027)	0.3204** (0.0413)	-0.0966** (0.0249)	-0.0968** (0.0228)
	14	ISP has digital connection	-0.3477** (0.0998)	-0.3681** (0.0888)	0.6612** (0.0328)	0.6612** (0.0222)
	15	missing	-2.2373** (0.1288)	-2.2417** (0.1342)	-0.2298** (0.0305)	-0.2297** (0.0242)
	16	ln(median household income)	0.0084 (0.0109)	0.0137 (0.036)	0.0147 (0.0111)	0.0147* (0.0072)
	17	# of business establishments per person	-6.052** (0.8402)	-6.0143** (1.7908)	-0.6304 (0.5024)	-0.6402 (1.8129)
	18	% population college graduate	0.0102 (0.0547)	-0.012 (0.216)	-0.0726 (0.1601)	-0.0719 (0.1986)
	19	% population urban	-0.0431** (0.0073)	-0.0418 (0.0371)	0.0059 (0.0257)	0.0058 (0.0264)
	20	% county population in different county 5 yrs ago	-0.1354 (0.1212)	-0.1353 (0.093)	-0.1422 (0.2004)	-0.1426 (0.1871)
	21	# of backbone providers	-0.0027** (0.0008)	-0.0026* (0.0011)	-0.0047** (0.0006)	-0.0047** (0.0006)
	22	Constant (σ_0)	0.0188 (0.0117)		0.0013 (0.0286)	
	23	log likelihood	-6071.5	-6072.1	-25,825.0	-25,825.0

+significant at 90% confidence level. *significant at 95% confidence level. **significant at 99% confidence level.

[a]Market-level unobserved heterogeneity is captured by the random intercept *C*: C~N(β_0,σ_0). The markets were randomly selected. For 500 markets, after omitting markets with 1 or 2 ISPs, we get a sample of 290 markets. For 1000 markets, after omitting markets with 1 or 2 ISPs, we get a sample of 694 markets. These estimates use the single market ISP model in Appendix Table 2 column 5 because unobserved heterogeneity is not identified in the multi-market model.

Appendix Table 5: Operational Sophistication, Survival, and Strategic Thinking

	Dependent Variable			
	τ^a	Survival^b	Survival^b	Survival^b
Have a Networking Maintenance Business	0.0798** (0.0219)	-0.0678 (0.0980)	-0.0840 (0.0985)	-0.0505 (0.0905)
Have a Web Design Business	0.0377* (0.0187)	0.0799 (0.0837)	0.0719 (0.0838)	
τ			0.205 (0.129)	0.212+ (0.128)
Constant	2.61** (0.0105)	0.315** (0.0467)	-0.220 (0.338)	-0.219 (0.338)
Log Likelihood	N/A	-799.4	-798.2	-798.5
R^2	0.022	N/A	N/A	N/A
# of observations	1213	1213	1213	1213

Uses the 1213 ISPs for which we have data on other activities that proxy for operational sophistication.
[a]OLS Regression; [b]Probit Regression
+significant at 90% confidence level. *significant at 95% confidence level. **significant at 99% confidence level.

Appendix Table 6: Technology Choices for Different Simulated Levels of Strategic Thinking

	Number of ISPs for each choice			
	Adopt neither	Adopt Rockwell Semiconductor's Technology (A)	Adopt US Robotics' Technology (B)	Adopt both
Everyone is Type-0	12.5	282.4	29.1	1909.0
$\tau = 1$	157.7	111.5	1258.5	705.3
$\tau = 2$	1238.4	127.2	599.8	267.6
τ =estimated from the data (the average is 2.62 though it varies across firms)	***1106.9***	***521.0***	***453.2***	***151.8***
$\tau = 3$	1242.6	511.6	371.0	107.9
$\tau = 4$	1544.7	397.4	242.1	48.8
$\tau = 5$	1723.6	296.7	187.4	25.3
Everyone is Type-1	96.9	10.6	2122.0	3.5

Simulations based on table 2 column 2 and 2,233 total ISPs in the data.
This table was used to generate Figures 1 and 2