Behavioral aspects of pricing

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Ec105

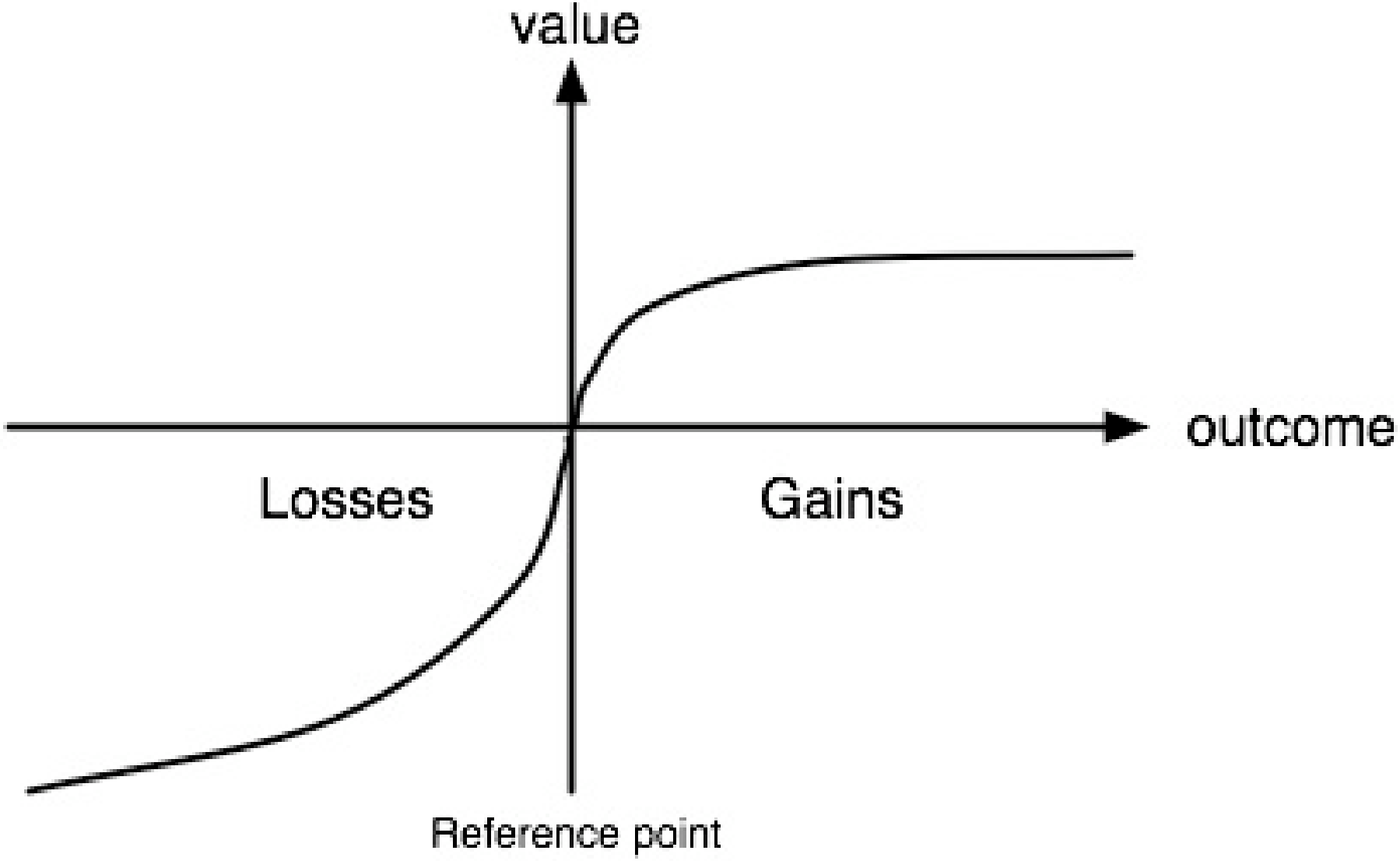
Behavioral aspects of pricing

- Inverse elasticity principle: explains how demand affects pricing
- But there are also "behavioral" aspects of pricing, where price can affect demand
  1. Price as "signal" of quality.
     - ($50 for iPhone X on eBay is "too good to be true")
     - Genuine vs. counterfeit products
  2. Reference-dependence:
     - consumers can be very price sensitive when prices move beyond a "reference price"
     - Food at restaurant seems "much more expensive" when price rises from 9.99 to 10.10
- Esp. important for products with both *use* and *status* functions.
- Low prices can be "dangerous" for firm.
  - If "riff-raff" start buying, ruin brand image
    - Apple (Jobs vs. Cook)
    - Tesla

Reference dependence

- or: loss aversion, prospect theory
- Basic idea:
  - Consumers evaluate choices relative to a (monetary) "reference point"
  - When reference point is price: suffer "loss" when price higher than reference price, gain when price lower then reference price
- Introspection: Black Friday
  - Amazon Kindle: usual price $99, BF price $49.
  - Let's say I don't buy it.
  - Once Black Friday is over, price back up to $99
  - Now I have to buy: experience reluctance to pay $99 (regret not having paid $49)
  - Might even prefer to buy Nexus for $99, to avoid regret with paying full-price for Kindle
- Graph:

Prospect theory preferences



Applications of reference dependence

- Housing markets: reluctance to sell house below purchase price
- (behavioral) Finance: disposition effect.
  - Investors "sell winners" but "hold losers"
  - (Feel esp bad about selling at a loss)
- Retail pricing: sales might be detrimental to long-run profits

Retail pricing: the effect of sales

- Under RD, sales might have detrimental long=run effects
- If consumers take sale price as RD, then post-sale they might be "doubly"-reluctant to buy product at normal price
- Abundant empirical evidence: "post-sale dip"
- But obviously, there are many alternative explanations
- Consider one specific example:

Hardware Store Pricing

- Scanner data from online hardware retailer
- In raw data, there is clear post-sale dip
- But is this RD?
- Reasonable alternative hypothesis: **stockpiling**
- Hardware items are durable goods: stock up during a sale, buy less after the sale.

Disentangling Loss Aversion vs. Stockpiling

- Focus on substitutes:
  - Under stockpiling: demand for discounted item as well as its substitutes fall after sale
  - Under loss aversion: demand for substitute increase relative to discounted item after sale
  - (Recall: Kindle vs. Nexus after BF)
- Picture
- Create substitutes from data, and estimate binary choice model with (parametric) RD preferences

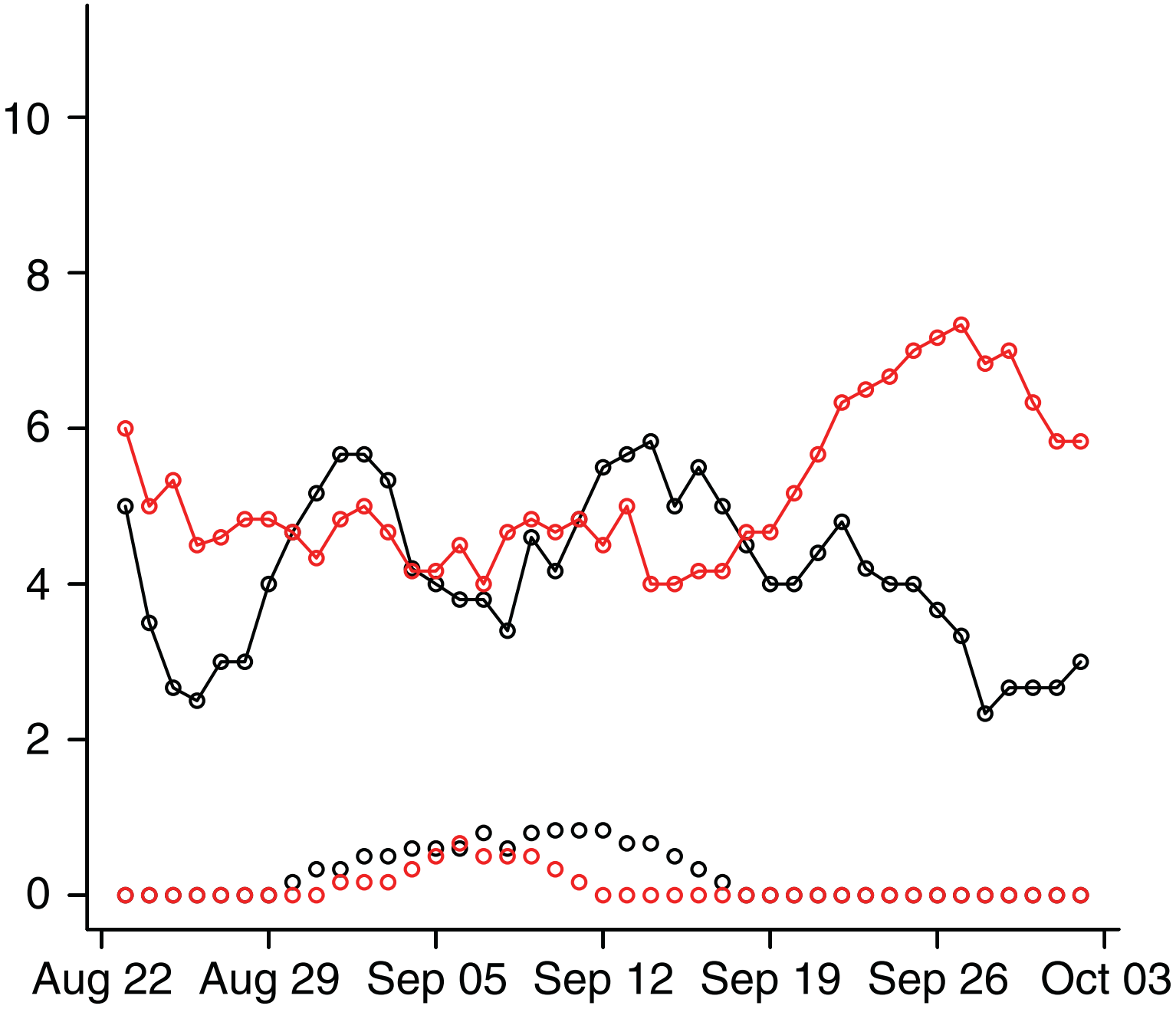


FIGURE 1. EXAMPLE OF SUBSTITUTION EFFECT: SALES OF $50 GIFT CARDS INCREASE AFTER DISCOUNT PERIOD FOR $100 GIFT CARDS ENDS

Table 2—Estimates of log-Share Equation for Product A: Top versus Bottom 50 Percent in Sales Volume (*Experience*)

Variable	Coefficient (1)	Coefficient (2)
top50	0.13648	0.11492
	(0.03497)***	(0.03615)**
$p_A - p_B$	−0.01204	−0.01052
	(0.00158)***	(0.00164)***
top50 × $(p_A - p_B)$	0.00980	0.00888
	(0.00156)***	(0.00162)***
$\lambda - 1$	0.00444	0.01635
	(0.00542)	(0.00696)**
top50 × $(\lambda - 1)$	−0.00362	−0.01200
	(0.00543)	(0.00698)*
cons $= v_A - v_B$	0.22385	0.23513
	(0.03499)***	(0.03612)***
Observations	21,492	21,053
Subst.-pair FX	Yes	Yes

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Taxicab labor supply

- "Reference income": drivers quit after reference income is reached (strong anecdotal evidence from interviews with drivers)
- Negative wage elasticities of labor supply: on (unexpectedly) high wage days, drivers work fewer hours.
- Camerer et al.; Crawford and Meng; Farber
- One problem: definition of "wage" (problem is that taxi drivers face a wage which is not only stochastic across days, but also stochastic within the day)

Reduced-form regressions: hours worked

Regress Log(shift duration) on wage + controls.
Define: Wage=total shift income/ hours worked.

	(1) OLS	(2) OLS	(3) IV	(4) IV
Log Wage	-0.106**	-1.160**	-0.485**	-0.135**
	(0.008)	(0.007)	(0.026)	(.023)
Weekday Dummy	-0.121**	-0.115**	-0.102**	-0.079**
	(0.002)	(0.001)	(0.002)	(0.002)
Rain > 1/10"	0.093**	0.090**	0.065**	0.041**
	(0.002)	(0.002)	(0.002)	(0.002)
Day shift	-0.127**	-0.355	-0.045**	-0.265**
	(0.002)	(0.006)	(0.004)	(0.008)
Driver FE	x	✓	x	✓
N	623,482	623,482	623,482	623,482

February 2012 data. Data record the final cumulative hours and average wage earned as of the last trip of each driver-shift. IV's are: the 25th, 50th and 75th percentile across all driver wages each day, as well as a dummy for day-of-week. Standard Errors clustered at the driver-shift level.

"non-equilibrium" beliefs

- Ample evidence that people, firms, are "overconfident"
- They are "smarter" than the rest of the population.
- Survey: 80% of drivers state that they drive "better than the average driver"
- A model of such beliefs:

Level-k and Cognitive Hierarchy (CH)

- Motivated by idea that everyone responds optimally to beliefs of how others will play.
- k: level of rationality. Defined recursively:
- Level 0: lowest level of rationality.
  - Players may just tell the truth (auctions, matching)
  - Players may randomize (number guessing games, centipede)
- Level 1: best respond assuming all other players are Level 0

...

- Level k: best respond assuming all other players are Level $k-1$
- Cognitive hierarchy:
  - A level-k player believes that all other players are *mixture* of levels $0, \ldots, k-1$.
  - Mixture typically Poisson $(0, 1, 2 \ldots; \lambda)$
- Important: in both LK and CH, beliefs about others are "wrong"

Some applications

- Goldfarb and Xiao: telecommunications entry with CH managers
  - Given parameters, beliefs for each rationality type can be computed recursively starting from level-0 ("naive" behavior)
  - Parameterize rationality type probabilities to depend on managerial ability variables

Table 4—Strategic Ability and Entry Coefficients ($N = 5{,}906$)

Variables	Main (1)	No covariates in Z (2)	Only manager characteristics (3)	Alternative treatment of missing variables (4)	No random effects (5)
Coefficients on strategic ability parameter $\log(\tau)$					
(1) Log(experience)	0.161		0.180	0.147	0.235
	(0.061)***		(0.053)***	(0.057)***	(0.080)***
(2) Manager attended school with SAT score above 1400	0.069		0.041	0.062	0.117
	(0.039)*		(0.034)	(0.038)	(0.052)**
(3) Manager has degree in economics or business	0.396		0.358	0.375	0.558
	(0.215)*		(0.162)**	(0.193)*	(0.253)**
(4) Log(experience) × Manager has econ/business degree	−0.165		−0.160	−0.157	−0.234
	(0.076)**		(0.057)***	(0.068)**	(0.089)***
(5) Manager has degree in engineering or science	−0.078		−0.136	−0.075	−0.119
	(0.026)***		(0.027)***	(0.028)***	(0.038)***
(6) Manager has graduate degree	0.029		0.098	0.028	0.024
	(0.027)		(0.023)***	(0.027)	(0.034)
(7) Log (firm age)	0.045			0.042	0.066
	(0.013)***			(0.013)***	(0.018)***
(8) Subsidiary	−0.138			−0.132	−0.215
	(0.035)***			(0.035)***	(0.052)***
(9) Privately owned	−0.129			−0.130	−0.173
	(0.030)***			(0.033)***	(0.047)***
(10) Venture capital	−0.005			−0.006	−0.021
	(0.054)			(0.052)	(0.060)
(11) Constant in τ	0.601	1.066	0.592	0.648	0.351
	(0.184)***	(0.043)***	(0.1600)***	(0.175)***	(0.249)
(12) Missing data dummy				0.025	
				(0.110)	
Coefficients on entry					
(13) Expected number of competitors	−0.655	−0.652	−0.685	−0.655	−0.545
	(0.074)***	(0.067)***	(0.076)***	(0.075)***	(0.051)***
(14) Place population in millions	2.059	1.933	2.309	2.000	1.815
	(1.267)	(1.253)	(1.310)*	(1.277)	(0.868)**

(*Continued*)

A. *What Drives Strategic Ability?*

In this subsection, 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 shows the coefficients for market attributes used in estimating the latent profitability of entry. Before turning to our analysis of manager- and firm-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.

Table 4—Strategic Ability and Entry Coefficients ($N = 5{,}906$) (*Continued*)

(15) HH income in $1,000	−0.005	−0.016	−0.013	−0.006	−0.007
	(0.027)	(0.024)	(0.025)	(0.027)	(0.018)
(16) Median age	−0.109	−0.103	−0.109	−0.114	−0.117
	(0.061)*	(0.055)*	(0.058)*	(0.060)*	(0.040)***
(17) Household size	−2.346	−2.020	−2.386	−2.363	−2.269
	(0.600)***	(0.576)***	(0.599)***	(0.598)***	(0.434)***
(18) Percent foreign born	4.115	4.071	4.115	4.279	4.208
	(1.885)**	(1.744)**	(1.781)**	(1.906)**	(1.232)***
(19) Percent African American	2.577	2.623	2.834	2.615	2.190
	(1.013)**	(0.947)***	(1.017)***	(1.016)**	(0.605)***
(20) Percent below poverty line	7.235	5.619	5.398	6.877	5.466
	(5.084)	(4.575)	(4.761)	(5.090)	(3.183)*
(21) GTE	1.964	1.945	2.035	1.962	1.806
	(0.660)***	(0.622)**	(0.636)***	(0.662)***	(0.441)***
(22) RBOC	1.196	1.239	1.366	1.176	1.193
	(0.576)**	(0.547)**	(0.577)**	(0.580)**	(0.365)***
(23) Log(number of establishments)	1.982	2.040	1.970	1.990	1.649
	(0.359)***	(0.344)***	(0.345)***	(0.359)***	(0.240)***
(24) Average number of employees per establishment	0.047	0.049	0.044	0.046	0.042
	(0.036)	(0.028)*	(0.033)	(0.036)	(0.020)**
(25) Percent establishments in manufacturing	−3.478	−3.922	−3.750	−3.512	−2.687
	(1.511)**	(1.293)***	(1.422)***	(1.504)**	(0.861)***
(26) Std. dev. of the market-specific unobservable	0.796	0.638	0.714	0.792	
	(0.194)***	(0.192)***	(0.196)***	(0.195)***	
(27) Constant	3.330	2.920	3.957	3.681	4.001
	(3.368)	(3.001)	(3.186)	(3.359)	(2.372)*
(28) Mean τ	2.59	2.90	2.83	2.59	2.36
(29) Minimum τ	1.96	2.90	2.23	1.66	1.57
(30) Maximum τ	3.41	2.90	3.38	3.41	3.48
(31) Log likelihood	−1,206.8	−1,292.9	−1,253.8	−1,202.6	−1,215.6

Note: Standard errors are reported in parentheses.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Rows 1 to 6 show the coefficients for manager-level characteristics in driving measured ability, and rows 7 to 10 show coefficients for firm-level characteristics. In discussing the results, we focus on three areas: experience, education, and ownership structure. The exponential specification of τ function means that coefficients in rows 1 to 10 can be interpreted as the percentage change in τ responding to a change in the covariate. Therefore, a positive coefficient $0.x$ means that the (discrete) type is drawn from a distribution with a (continuous) Poisson parameter that is x percent higher and the manager will, therefore, on average, be of higher ability.

Experience.—Experience is widely viewed as an asset for managers. It is emphasized in manager biographies and in company annual reports. Laboratory research has shown experience is positively correlated with ability in beauty contest games (Robert L. Slonim 2005), and other research has documented a relationship between experience (measured at the firm or manager level) and behavior. Our results support

Table 6—Firms with a Higher τ Are More Likely to Exit the Industry Early

	Survive in sample to 2002		Alternative definition of survival to 2002		Log revenue in 2002		Log local phone revenue in 2002	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
τ[a]	0.345	0.417	0.294	0.416	2.496	1.778	2.422	2.003
	(0.184)*	(0.233)*	(0.160)*	(0.199)**	(1.251)*	(1.171)	(1.245)*	(1.308)
Log(firm age *in* 1998)		−0.0050		−0.037		−0.208		−0.461
		(0.074)		(0.063)		(0.405)		(0.369)
Log(employees in 1998)		−0.017		−0.005		0.493		0.549
		(0.023)		(0.021)		(0.150)***		(0.134)***
Constant	−0.467	−0.538	−0.096	−0.299	11.536	11.199	10.719	9.752
	(0.447)	(0.550)	(0.401)	(0.494)	(3.008)***	(2.686)***	(3.106)***	(3.092)***
Observations	96	90	96	90	48	46	46	44
R^2	0.05	0.07	0.04	0.06	0.14	0.34	0.13	0.40

Notes: All columns use linear regression. Heteroskedasticity-robust standard errors in parentheses.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
[a] τ is a generated regressor calculated from the coefficients in Table 4 column 1. We follow procedures outlined in Jeffrey M. Wooldridge (2002) to adjust standard error bias due to uncertainty in the estimate of τ.

an industry with a high turnover rate and that we 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.

C. *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.[22]

Table 6 shows the results. The key 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: (i) survival as defined by appearing in the 2002 NPRG reports, (ii) survival as defined by not having an accessible public record of exit through failure, (iii) revenue (conditional on survival), and (iv) local phone service revenue (conditional on survival).

Because we predict the value of τ from a simple exponential 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

[22] 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.