No Exit:
Failure to Exit under Uncertainty

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Delayed exit is a substantial economic problem. Studies indicate if VCs exited ventures optimally, returns would triple, and if corporations divested underperforming business units, shareholder wealth would increase 13.6%. A prevalent explanation for delayed exit is behavioral biases associated with escalated commitment. In general however exit will exhibit inertia even absent bias. This arises both from decision maker efforts to avoid Type I error while discovering the long run prospects of an endeavor (passive learning) and from the option value of exit. Solutions to exit delays differ depending upon which source predominates, yet empirical tests to date have not disentangled the relative importance of these sources. We characterize exit delay in the population of U.S. banks between 1984 and 1997, and examine its causes. We find that a substantial proportion of exit occurs beyond 'rational' benchmarks that incorporate option value. While the bulk of this delay appears to represent efforts to minimize Type I error, there is also evidence of the behavioral biases associated with escalated commitment.

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I. **Introduction**

The management and economics literatures pay substantial attention to entry decisions: what industries, markets and products firms should enter/introduce. Relatively little attention is paid to the obverse--exit. For example an ABI search on "entry" brings up 1553 articles whereas a search on "exit" brings up an order of magnitude (160) fewer articles. This is curious since in equilibrium entry and exit should occur at roughly the same rate. Indeed, in the US, 3.0 million employer firms were created between 2000 and 2005, while 2.8 employer firms died over the same period.

If exit decisions were trivial, the lack of attention in the literature would be understandable, but there is substantial evidence that firms and managers struggle with exit decisions. A particularly salient anecdotal example is General Motors, whose shareholder equity reached -$50 billion and only belatedly shuttered uncompetitive brands such as Pontiac, Oldsmobile, and Mercury. There is academic evidence as well: Guler (2007), for example, finds the distinction between high performing and low performing venture capitalists (VCs) is not their ability to choose successful ventures, but their ability to terminate unsuccessful ventures. She estimates if VCs exited ventures optimally, their returns would triple. A related exit problem that has been well-studied in the literature is the diversification discount. The average diversified corporation trades at a discount of 20% relative to its breakup value (citation), indicating that substantial shareholder wealth could be created if firms could exit their activities optimally.[1]

The main body of theory addressing exit delay is the organizational psychology literature on escalation of commitment (Staw 1976). Escalation of commitment refers to a class of phenomena with three characteristics: investment toward a goal, repeated decisions in the face of negative feedback, and uncertainty about outcomes. Under these conditions, actors seem slow to abandon their initial decisions.

[1] The problem of course is two-sided. It is not simply the case that firms should exit earlier than they do. There are both type I and type II errors. Thus the complementary problem is that firms exit the wrong investments. Chesbro and Rosenbloom (2002) for example find the market capitalization of projects Xerox exited is three times that of Xerox itself.

Although behavioral biases may contribute to delays under uncertainty, exit will exhibit inertia even absent these biases. Such theories of “rational” delay arise in economics to explain deviations from Marshallian exit, where Marashallian exit is defined as the point at which the present value of the expected future stream of profits fall below zero. Jovanovic (1982), for example, treats excess entry and exit delay as outcomes of ability uncertainty.[2] Firms exit if their ability is below the market threshold, but they must enter and operate in the market to learn their ability. Since firms receive noisy signals about their underlying ability, it takes time to detect their underlying profits are negative. Delay relative to the Marshallian benchmark also arises from real options associated with exit. There are two such options. First is the option of staying in the market to avoid the re-entry cost if the market improves (Dixit 1989). Second is the option to cut losses in the future (Ryan and Lippman 2003). Under both options, firms will remain in the market even though the expected present value of continuing operations is negative.

The discussion above suggests that both economics and organizational psychology inherently view exit delay as a problem of decision making under uncertainty. Accordingly, tests examining delay as a function of uncertainty levels or signal volatility tend to support either view, and are unable to disentangle the two effects. However, since the theories have differing prescriptive implications for government policy and firm strategy, it is important to discriminate between them.

We explore the relative importance of these sources of exit delay by investigating the timing of exit of U.S. banks between 1984 and 1997. In particular, we seek to decompose exit delay into "rational" attempts to maximize firm value in the presence of noisy performance signals versus behavioral bias in responding to those performance signals. We chose this context for a number of reasons. First, the principle cause of bank failure is high cost relative to rivals, thus the failure mechanism matches that in economic theories of exit. Second, the FDIC provides complete

[2] Note that ability uncertainty alone is insufficient to generate excess entry. Camerer and Lovallo (1999) show that absent overconfidence in ability, there is no excess entry.

quarterly financial data for the full census of US banks, thus we know what signals each bank observes, and we can also estimate "relative cost" in each period (the signal they are trying to detect). Finally, banks are distributed across fifty US markets which differ in the levels of market uncertainty (demand volatility) and ability uncertainty (cost dispersion). Accordingly we can estimate the impact of each type of uncertainty on exit delay.

Our results in that setting indicate that exit conforms to a rational model of passive learning (efforts to minimize Type I error while firms detect their true type), rather than to a model which values options to either avoid entry costs or cut losses in the future. Indeed 85% of exit occurs beyond the optimum associated with the RL option. However, we also find considerable evidence of behavioral bias. Entrepreneurs in this setting have asymmetric responses to positive versus negative profits. These results have implications for both firm strategy and public policy. The paper proceeds as follows. First, we review the economics and organization psychology literature on exit delay. Next, we develop an empirical model to decompose the various effects. We describe the empirical test of that model then discuss results and implications for both firm strategy and public policy.

2. Theories of exit delay

Exit decisions occur in many contexts and at many levels of analysis: venture capitalists exit from ventures, firms exit from business units or markets and abandon R&D projects, employees leave firm, individuals sell stock and spouses leave marriages (Thompson 2008). While these decisions share common elements, they tend to have idiosyncratic elements as well. The easiest means to compare them is to think of exit decisions as having nested complexity, as shown in Figure 1.

Insert Figure 1 about here

At the core is "ideal" exit by a unitary and unbiased actor under perfect information. This ideal can be captured in either decision theoretic logic (Marshallian exit) or game theoretic logic (Ghemawat and Nalebuff 1985, Fudenberg and Tirole 1986). Complexity increases as we introduce uncertainty. This introduces problems of recognizing underlying states (e.g,. Jovanovic 1982) and efforts to optimize real options (e.g., Dixit 1989, Ryan and Lippman 2003). The next level of complexity retains solitary actors with perfect incentives, but introduces human decision makers who are subject to behavioral bias. Finally at the greatest level of complexity are multiple decision makers, as in the case of venture capital funds and public firms. Multiple decision-makers adds the classic problems of organizational economics, such as agency problems of non-owner managers, and problems of joint decisions with multiple stakeholders.

Because we are interested in minimizing avoidable delay, we want to decompose delay into its rational versus biased components. We characterize the extent to which exit timing conforms to the real options optimum, versus delays associated with behavioral bias.[3] In the real-world setting bank exit, the behavioral effects that we uncover are the result of a combination of individual level biases, group level biases, and, potentially, agency problems. Although we cannot parse precisely between these effects,

2.1. Exit under perfect information

The simplest form of exit under perfect information is Marshallian exit. Here firms exit a market if the present value of the stream of future operating profits falls below zero (alternatively revenues are less than the sum of operating costs plus the carrying cost of sunk investment). A broader interpretation of exit under perfect information considers opportunity cost. Here firms exit when the net present value of profits is less than the opportunity cost of resources. In the case of multibusiness firms, opportunity cost includes alternative uses of resources (Penrose 1959, Levinthal and Wu 2010). In the case of entrepreneurs, opportunity cost also includes their wages in alternative employment. Marshallian exit

[3] In the real-world setting bank exit, the behavioral effects that we uncover are the result of a combination of individual level biases, group level biases, and, potentially, agency problems. Although we cannot parse precisely between these effects, our work represents an important first step in this area.

takes all market conditions and firm behaviors as given and provides a benchmark with which to compare other theories of exit.[4]

2.2. Noisy Selection/Passive learning

We focus first on the implications for exit timing in Jovanovic's (1982) theory of noisy selection. The theory considers an atomistic industry (infinite number of firms and potential entrants, each of measure zero so that each is a price taker). Firms and potential entrants know the entire equilibrium price sequence and the distribution of firm costs, but potential entrants face ex ante uncertainty regarding their own cost. Firms pay a sunk cost to enter the market, then begin receiving noisy signals about their true cost. Firms exit if and when they learn the expected value of profits (given updated beliefs) is below the opportunity cost of exit. Jovanovic's model generates an equilibrium in which price is constant over time and entry and exit occur in each period.

This model is appealing for a number of reasons. First, its assumption regarding known cost distribution, but ex ante uncertainty regarding own cost matches empirical reality in the banking industry (Wu and Knott 2007). Second, its expectations regarding the size distribution of firms match empirical reality across a number of industries. Finally, the model anticipates the churn characterizing most US industries. On average firms enter the economy at an annual rate of approximately 11% of incumbents and exit at a rate of approximately 10% of incumbents.

Because Jovanovic is interested in patterns of entry, exit and growth in an industry, his propositions pertain to aggregate dynamics. Thus he does not explicitly model the firm-level decisions. There are two interpretations of how these firm-level decisions are made. One interpretation is that firms solve a stochastic dynamic programming problem where they maximize expected value in each period (by

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[4] In addition to the Marshallian perspective are game theoretic models that consider firm interaction in declining industries (Ghemawat and Nalebuff 1985, Fudenberg and Tirole 1986). These examine the order and timing of exit from markets where industry profits are negative for two firms, but would continue to be positive for a single firm. Since the banking industry prior to 1997 was comprised of hundreds of banks per state, game theoretic models are likely to have limited predictive ability in our setting.

choice of exit/remain) assuming they value maximize in all subsequent periods. This is the interpretation in Pakes and Ericson (1998) who test whether firms conform to a model of passive learning (Jovanovic 1982) versus a model where firm cost evolves over time in response to investments in process innovation (Nelson & Winter 1982, Ericson and Pakes 1995).

An alternative interpretation of the firm-level decision is that entrepreneurs solve a simple detection problem. Firms exit when the liklihood of making a Type I error (exiting when their underlying condition is profitable) falls below a given confidence threshold.

We treat these in reverse order.

2.2.1. Minimizing Type I Error (Passive Learning)

Jovanovic's model consists of a pair of sufficient statistics: the number of signals regarding firm cost and the mean value of those signals. This suggests a simple detection model where the firm wants to minimize type 1 error as it tries to determine whether its cost is above the market threshold and therefore unprofitable. This detection problems is equivalent to achieving statistical significance in econometric tests. The simplest test of statistical significance in this context is a t-test of unequal variance, where a firm wants to achieve a given confidence level, e.g., 95%, that it's profits are negative.

$$t = \frac{\mu_1 - \mu_2}{\sqrt{\frac{s_1^{\,2}}{n_1} + \frac{s_2^{\,2}}{n_2}}} \qquad (1)$$

The t-statistic, and hence statistical significance (detection ability) increases with the difference between the firm's underlying cost, μ_2, and the market cost threshold, μ_1, in the number of firms, n_1, and the number of focal firm profit signals, n_2, but decreases in the variance of firm cost distribution, s_1, and volatility of the focal firm's cost signal, s_2.

2.2.2. Stochastic Dynamic Programming Problem

While Pakes and Ericson (1998) are more explicit about firm-level mechanics, their goal (like that of Jovanovic) is explaining aggregate phenomena. Accordingly the best firm-level model of exit as a stochastic dynamic programming problem comes from Ryan and Lippman (2003). Ryan and Lippman (RL) present a model of a firm's decision to exit a project given noisy signals about its underlying profits. Here forward we refer to *firms* rather than RL's *projects*. The model assumes firms are of two types: with probability p_0, firms are profitable, and have underlying profit rate, μ_H. With probability $1- p_0$ they are unprofitable, and have underlying profit rate, μ_L. The underlying profit rate is unobservable, but firms receive noisy signals of profits over time. The signal comprises the underlying rate plus a noise component with variance σ^2. Cumulative profits, X_t, thus exhibit Brownian motion with drift μ and variance σ^2. The firm maximizes expected discounted profit in each period by choice of exit.

The firm knows the value of μ in each of the two states and the aggregate probability, p_0 of being in the high state, but does not know is own state. The firm's posterior estimate of being in the high state at time t, P_t, is a function of cumulative profits, X_t, signal volatility, σ, the profit rates in each state, μ, and the discount rate, α, but is independent of the pattern of profits. RL derive the optimal stopping time, t, as the first time at which cumulative profits, X_t, fall below threshold :

$$X_t \leq -\left[\frac{\sigma^2}{\mu_H - \mu_L}\log\left(\frac{\mu_H p_0(\gamma+1)}{-\mu_L(1-p_0)(\gamma-1)}\right)\right] + \frac{\mu_H + \mu_L}{2}t \qquad (2)$$

with

$$\gamma = \sqrt{1+\frac{8\alpha\sigma^2}{(\mu_H - \mu_L)^2}}$$

Ryan and Lippman generate a number of comparative statics from their model regarding the timing of exit for low type firms (those for whom exit is inevitable):

- Exit delay is increasing in cumulative profits, X_t, and cost dispersion, $\mu_H - \mu_L$

- Exit delay is decreasing in ex ante probability of success, P_0, interest rate, α, and ex post profit volatility, σ.

While the passive learning model and the RL model share predictions regarding cumulative profits, opportunity cost, interest rate and cost dispersion, they generate opposing predictions regarding the profit volatility. In particular, profit volatility *extends* delay in the passive learning model, while *decreasing* delay in the RL model.

The intuition for the opposition is as follows. Low profit volatility contributes to higher signal-to-noise ratio, making detection easier. In the passive learning model, detection translates to earlier exit. Ironically, the very conditions facilitating detection of a firm's underlying state are also the conditions increasing the value of the exit option. Since each signal is highly informative, the value of waiting for an additional signal is high, in that it increases the ability to cut losses in the future.

Empirical support for Jovanovic's model of noisy selection comes from a number of sources. Support at the behavioral level comes from Camerer and Lovallo (1991) who show that uncertainty and overconfidence generate excess entry in a lab experiment, and from Wu and Knott (2007) who show that cost dispersion (opportunity for overconfidence) increases entry in real markets. Support at the aggregate level comes from Pakes & Ericson (1998) who find that dynamics in retail settings match passive learning, but those in manufacturing match a model of exploration (Nelson & Winter 1982, Ericson & Pakes 1998)

2.3. Real Options and Sunk Costs of Entry

RL is essentially a real options model where the option is to cut losses under uncertainty about own cost. An alternative real options model comes from Dixit (1989). Dixit is an effort to explain hysteresis in entry and exit decisions—entry which occurs at prices above the Marshallian entry threshold and exit which occurs at prices below the Marshallian exit threshold.

In Jovanovic and RL the exit problem is determining whether own cost is below market threshold in a world where a firm's costs are fixed and the market price sequence is known . The uncertainty pertains to own cost and the firm attempts to infer its cost from noisy profit signals. In Dixit, there is no uncertainty regarding own cost. Rather there is uncertainty regarding market price, P, which follows Brownian motion: $dP/P=\mu dt+\sigma dz$.

In each period the firm maximizes its net present value given the current price and an assumption of optimal decisions thereafter. Because firms incur sunk costs, k, on entry, they find it worthwhile to remain in the market when profits are negative to avoid repaying entry costs if prices improve. As in RL, the dynamics reduce to a simple decision rule, where firms exit when market price, P, falls below the exit threshold, P_L.

Dixit generates comparative statics numerically. In general, delay increases (P_L decreases) in: sunk cost, k, demand growth, μ, and demand volatility, σ. Delay decreases (P_L increases) in the interest rate, ρ. This leads to equilibria with hysteresis in entry versus exit triggers: the entry trigger is above Marshallian trigger price (operating cost plus the carrying cost of sunk investment), while the exit trigger is below Marshalling trigger price (operating cost plus exit cost).

It is worth noting that while Dixit and RL both model real options associated with exit, they reach opposing predictions regarding signal volatility. In RL signal volatility decreases the value of the venture because it impedes learning. In contrast, for Dixit (1989) volatility increases the expected profits due to greater likelihood of a future high price period, which in turn increases the value of the exit option. Thus in addition to testing for the extent and composition of exit delay, we can implicitly test whether exit behavior conforms to Dixit versus RL option values.

Empirical support for the behavioral implications of the Dixit model comes from Ansic & Pugh (1999) who demonstrate via lab experiment that sunk cost and exchange rate uncertainty delay exit, and from Berger, Ofek, Swary (1996), who show that investors value abandonment options. Empirical support for the aggregate implications come from Moel and Tufano (2002) who find evidence of hysteresis in the opening and closing of gold mines, and from Campo (2004), who finds evidence of hysteresis in foreign export activity.

2.4. Escalation of commitment

The organizational psychology literature most relevant to exit is Staw's work on escalation of commitment (Staw 1976, Staw and Ross 1978). Escalation of commitment describes a class of phenomena sharing three features: investment toward a goal, repeated decisions in the face of negative feedback and uncertainty about outcomes. A number of theories have been advanced to explain escalation of commitment. Viewed from a Bayesian perspective, some of these pertain to strength of priors; others pertain to interpretation of new information for updating posteriors.

Mechanisms affecting the priors include the *sunk cost fallacy* (Thaler 1980)--the tendency to avoid losses from sunk investments despite their irrelevance, *anchoring* (Tversky and Kahneman 1974)-the tendency to rely too heavily on initial reference points, *status quo bias* (Samuelson and Zeckhauser 1988)--the tendency to maintain a behavior unless there is a compelling reason to change, and *overconfidence* (Roll 1986)--the tendency to overestimate one's own ability.[5]

Mechanisms affecting the interpretation of new information include self-serving *attribution bias* (Miller and Ross 1975)--the tendency to treat successful outcomes to one's own skill and unsuccessful outcomes to bad luck, *confirmatory bias* (Lord, Ross and Lepper 1979) -- the tendency to interpret information in a way that confirms preconceptions, and *motivated reasoning* (Kunda 1987)--the tendency to accept desirable information, but scrutinize undesirable information.

The finance literature has adopted behavioral theory as a means to explain asset pricing distortions, beginning with Roll's (1986) hubris hypothesis of acquisition prices. While Roll applied the hubris construct to firm behavior, more recent work (Daniel, Hirschleifer and Subrahamanyan 1998,

[5] There is confusion in the literature regarding overconfidence and optimism In some instances overconfidence refers to the accuracy of one's estimates (Fischoff, Slovic and Lichtenstein 1977); in others it refers to overestimating own ability. There is also similar confusion regarding optimism: optimism regarding outcomes generally (Heath and Tversky 1991), versus optimism about outcomes of own effort. We follow the convention that overconfidence refers to estimates of own ability.

Barber and Odean 2001 and 2002) has applied the notion of overconfidence to explain anomalous investor behaviors such as excessive trading. One question is whether overconfidence is inate or developed. Gervais amd Odean (2001) argue overconfidence, much like escalation of commitment, is developed through self-serving attribution bias applied to sequential decisions with noisy feedback.

Choi and Lou (2007) test the Gervais and Odean hypothesis using data from active fund managers. They operationalize overconfidence as both deviations from a benchmark portfolio and turnover ratio; they operationalize self-serving attribution bias as volatility of past returns, and they operationalize true ability as subsequent returns. They find a) that volatility increases both measures of overconfidence, and that its effect on overconfidence is larger than true ability (past performance). The logic for using volatility as the measure of self-serving attribution bias is the asymmetry in response to feedback—individuals revise their self-perceptions upward more in response to positive signals than they revise self-perceptions downward in response to negative signals. The concern with this implementation is that volatility is also a measure of noise—thus self-serving attribution bias cannot be distinguished from rational delays associated with passive learning and the option value of exit. In addition to the concern with the proxy, is the concern that fund managers are agents, thus they have asymmetric incentives—rewards are higher for positive outliers than punishments for negative outliers.

Thus the behavioral theories suggest two forms of bias relative to a rational model of exit. First is the weight of priors. Second is asymmetric updating of new information. The mechanisms affecting priors are anchoring, status quo bias and overconfidence. Each of these will increases the weight of priors as well as delay relative to a rational model. The mechanisms affecting updates are confirmatory bias, attribution bias and motivated reasoning. Each of these implies that actors discount negative information relative to positive information. Thus they imply asymmetric values for the weights of updates. The theories anticipate that the update on positive signals should be larger than that on negative signals.

3. Data

We conduct our tests in the banking industry following de-regulation. The industry was chosen because it exhibits substantial entry and exit (on an absolute basis rather than a relative basis) (see Figure 2), and because the mechanism of exit (inefficiency) matches the failure mechanism in economic models. In addition our focus on a single industry eliminates heterogeneity in "amenity potential" (Demsetz and Lehn 1985) and opportunity costs that stem from differences in the composition of human capital across industries (Gimeno, Folta, Cooper and Woo 1997). In particular, the human capital necessary to gain a charter is banking specific, thus the outside employment opportunity under failure is banking executive. Moreover banking is highly professionalized, thus the amenity potential and psychic benefits of banking entrepreneurship are comparable across firms.

Insert Figure 2 about here

Finally, during our period of investigation the industry was fragmented with localized competition. Fragmentation is important because it allows us to compare discrete markets within the same industry. Thus we can compare differences in ex ante uncertainty while controlling for other factors affecting cost across distinct industries. We can also control for differences in level of demand through differences in economic conditions across markets. Finally, the industry has comprehensive quarterly financial data for the full census of insured banks (over 99% of all banks).

Data for the study come from the FDIC Research Database which contains quarterly financial data for all banks filing the “Report of Condition and Income” (Call Report). We restrict attention to the 8082 banks who exit during the period. There are two forms of exit in this setting: failure (1322 firms) which follows the FDIC definition of a “paid out” or a “forced merger”, and unforced merger (6627 firms) who merge voluntarily.

From the set of raw variables in the data base, we derive the variables used in the analysis below. The dependent variable is implicitly the number of quarters that the firm is under observation until failure. (Figure 3 is a histogram of periods until failure).

Insert Figure 3 about here

The *cost* variable is the measure of firm cost relative to a global frontier (derived in Knott and Posen 2005). Our measure for *p-zero*, (P_0, the a priori probability of being profitable) is the ratio of failed firms to all firms in each market. Our measure of *cost dispersion* is the standard deviation of relative cost in the market. Our measure of *ex post uncertainty* is the firm specific standard deviation of profits for the periods the firm is in the market. *Cumulative profits* is the running sum of quarterly net income ($1000). The options variables are *re-entry cost* and *demand volatility*. *Re-entry cost* is the mean value of financial and physical assets for firms entering market j at time t. This measure is estimated for each market in each year and lagged one year. *Demand growth* is the coefficient on time (years) in market-specific regressions of demand (loans). *Demand volatility* is measured as the RMSE from the growth regression. The behavioral variables are *cumulative positive profits* (the running sum of profits over periods in which they are positive) and *cumulative negative profits* (the running sum of profits over periods in which they are negative). We control for o*pportunity cost* using market-year wage derived from the FDIC data. The time-varying *market characteristics* (population, building permits, market size and firms in market) are derived from census data. The measures control for differences in economic conditions and market structure across markets. We control for economy wide conditions affecting opportunity cost (primarily the cost of capital) and the option value of remaining in the market (primarily the opportunity to be acquired) through year effects. These data are summarized in Table 1.

Insert Table 1 about here

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4. Analysis

To decompose exit delay into its rational and behavioral components, we examine exit across fifty markets in the US banking industry. We begin by modelling exit timing using an accelerated failure time (AFT) model which accomodates rational detection of underlying profits, opportunity cost, the option value of cutting losses and avoiding re-entry costs, plus behavioral bias. This approach enables us to test several of the implications of models of exit timing and delay. We then attempt to examine exit delay directly by comparing the time of actual exit to benchmarks derived from the RL and passive learning models.

4.1. Estimating Time to Exit

We first test the implications of the RL and other models for the time to exit of all banks that fail between 1984 and 1997. Equation 3 models exit timing as a function of firms' true cost, market cost dispersion, profit volatility, the ex ante probability of being in the high state in market j (P_{oj}), and the firm's cumulative profits. We also include opportunity cost (mean industry wage in market j), and the option value of re-entry (the mean cost to enter market j at time $t-1$ together with demand volatility). We control for time varying market characteristics, X_{jt} and year effects, δ_t. The year effects capture economic conditions, e.g., interest rates and quality of the acquisition market, that vary over time.

In addition to these rational components we test for the behavioral biases associated with escalation of commitment. We capture biases affecting updates (confirmatory bias, attribution bias and motivated reasoning) by replacing cumulative profits with its positive and negative components (*cumulative positive* and *cumulative negative*). Biases affecting priors (anchoring, status quo bias and overconfidence) can't be estimated because their effects are confounded by other factors in the intercept.

$$t(exit)_{ij} = \beta_0 - \beta_1 c_{it} + \beta_2 \sigma_j (c_{it}) + \beta_2 \sigma(\Pi)_{it} + \beta_3 \Sigma_t(\Pi)_{it} + \beta_4 \Sigma_t(\Pi>0)_{it} + \beta_5 \Sigma_t(\Pi<0)_{it} + \beta_6 P_{0j}$$
$$+ \beta_7 K_{jt} + \beta_8 Q_{jt} + \beta_8 \sigma_j (Q)_{jt} + \beta_9 w_{jt} + X_{jt} + \delta_t \qquad (3)$$

where:

c_{it}	=	firm cost relative to a global frontier (Knott and Posen 2005)
$\sigma_j (c_{it})$	=	cost dispersion in market j
Π_{it}	=	firm profits
$\Sigma(\Pi)_{it}$	=	cumulative profits
$\Sigma(\Pi_{it}>0)$	=	positive cumulative profits

$\Sigma(\Pi_{it}<0)$	=	negative cumulative profits
K_{jt}	=	re-entry cost (mean assets for firms entering market j at time t)
Q_{jt}	=	demand (loans) growth in market j
$\sigma_j(Q_t)$	=	demand volatility in market j
w_{it}	=	market wage
X_{it}	=	vector of time varying market characteristics

Note there are three real options in banking that potentially offer value of remaining in the market with negative NPV. The first two options are the RL and Dixit models discussed previously. We test these directly. The third option in this setting is acquisition by a bank holding company. There was substantial consolidation in the industry during the period we examine (Figure 4). We control indirectly for this option value via year effects.

Insert Figure 4 about here

We test equation 3 using an AFT model (Stata procedure streg). The model implicitly tests the impact of correlates relative to mean failure time. Accelerated failure time models are used in health care studies where the field is interested in expressing the impact of treatments as extended life span rather than hazard of death. Positive coefficients are interpreted as extending time to fail. AFT models are parametric, thus we must specify a distribution for the error term. Our primary distribution is Weibull, however we also test alternative forms.

Under all models we expect exit time to decrease with own cost, and with opportunity cost (mean wage). Under both passive learning and RL we expect exit time to increase with cumulative profits and cost dispersion. Under RL we also expect exit time to increase with the ex ante likelihood of being profitable, P_0. Under passive learning we expect exit time to *increase* with profit volatility. Conversely, under RL we expect exit time to *decrease* with profit volatility. Under Dixit, we expect exit time to increase with re-entry cost, demand growth and demand volatility.

Finally, we test for behavioral bias by decomposing cumulative profits into its negative and positive components. Under escalated commitment (confirmatory bias, attribution bias and motivated reasoning) we expect the coefficient for positive profits to be greater than that for negative profits. Under rational exit the coefficients on negative and positive profits should be equal.

The expectations across all models are summarized in Table 2.

Insert Table 2 about here

We present the results of these estimations in Table 3. The results support both a model of noisy selection/passive learning and behavioral bias, but fail to support either the RL or Dixit models of option value to future exit.

Prior to discussing our main test, we first present a model of controls as a basis for comparison. Model 1 includes controls for firm cost, opportunity cost and time varying market characteristics. The model indicates exit accelerates with increases in firm cost as well as opportunity cost. The coefficients on both *cost efficiency* and *mean market wage* (the best outside option for bank entrepreneurs) are negative and significant, indicating that firms exit more quickly when they are high cost (due to a stronger signal) and when their outside option improves. Both results are as expected. Moreover both results hold across all models. While we include four time-varying market controls, these are highly correlated, and thus not separately interpretable.

Model 2 tests passive learning (efforts to minimize Type I error) versus the RL model of option value to cutting losses. The coefficients for *cumulative profits* and *p-zero* are positive and significant as expected under both models. The results for the noise components allow us to critically test the RL model against the passive learning model. Exit time is increasing in (delayed by) both market *cost dispersion* and firm *profit volatility*. This is as expected under passive learning since both *cost dispersion* and *profit volatility* represent noise that impedes firms' ability to detect underlying profits. While we also expect exit time to increase with *cost dispersion* under RL, we expect it to decrease with *profit volatility*. Thus results favor the passive learning model over the RL model of option value to exit in the future.

Insert Table 3 about here

Model 3 tests the option value of avoiding re-entry cost. Exit is accelerating in both *re-entry cost* and *demand volatility*. While the coefficient on re-entry cost is negative and significant, that on demand volatility is insignificant. Both results conflict with predictions under the Dixit options model. Expectations under the options model are that both coefficients would be positive and significant.[6]

Model 4 adds the behavioral test to Model 2.[7] To test for behavioral bias we look for asymmetry in firm response to positive signals versus negative signals. We accomplish this by decomposing *cumulative profits* into *positive profits* and *negative profits*. The coefficients on both measures are positive and significant indicating that positive profits delay exit, while negative profits accelerate exit, as expected. What is more interesting is that the coefficient on positive profits is 15.8 times that of negative profits. This difference is significant at the 0.0001 level. Thus firms significantly discount negative signals relative to positive signals. This is as expected under all three updating mechanisms associated with escalated commitment: confirmatory bias, attribution bias and motivated reasoning. Model 5 tests the behavioral theories as a standalone model and achieves the same results.

In summary, our results support a model of passive learning (minimizing type 1 error) plus escalated commitment. There is no evidence that firms in this setting recognize the option value to exit (either the option to cut losses or the option to avoid re-entry cost). One interesting exercise would be to compare the power of the rational components to the behavioral components in explaining exit delay. While the AFT model doesn't provide R-squared, we obtain a relative sense of model fit by comparing reduction in log-likelihood. The rational model (2) offers a 21.9% reduction in log-likelihood relative to the model of controls (1). In contrast the behavioral model (5) offers an 8.3% reduction. Thus the rational model appears to offer three times the explanatory power of the behavioral model.

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[6] Note these results also conflict with the *sunk cost fallacy* (Thaler 1980)

[7] Note we remove profit volatility from this model because its effects are equivalent to decomposing profits into their positive and negative components.

4.2 Exit Relative to the RL Benchmark

The above tests examine the positive question of how firms *do* behave. An important companion is the normative question of how they *should* behave. To examine that informally, we construct the RL threshold (equation 2) for all firms in our sample (the Dixit options model is less relevant when there are opportunity costs whose value exceeds the option to avoid re-entry cost, as is the case here).[8] To construct the threshold in each market j, we compute P_{0j} as the share of surviving firms in that market, and compute μ_{Hj} and μ_{Lj}, respectively as the mean cost of surviving and failing firms in the market. We use σ_i for volatility of focal firm profits (as described in the econometric test) and set the discount rate, α, at 10%. We then determine the period in which firm's cumulative cost crosses this threshold. This construction is subject to the caveats that the RL threshold is based on a binomial cost distribution with continuous sampling, while our cost data is normally distributed and discretely sampled. Finally we compute the difference between the actual exit period and optimal exit period. A histogram of those differences is presented in Figure 5. The figure indicates 85% of exits occur beyond our calculation of the RL optimum. This captures the extent of delay.

Insert Figure 5 about here

4.3.Exit relative to the passive learning benchmark

While RL is the optimal decision rule in this setting, it is also worth investigating how closely firms conform to an alternative rational decision rule: minimizing type I error. Following the discussion in § 2.2.1, we measure the firm's confidence, in a statistical sense, that it is truly uncompetitive by the

[8] There are some distinctions between the RL model assumptions and characteristics of our data. In particular the RL model characterizes optimal exit using continuous draws of profit signals from a binomial distribution. In contrast our data reflect discrete draws from a normal distribution. The timing of draws is presumed innocuous. The larger concern is treating all firms above threshold as sharing the same profit rate, and treating all firms below threshold as sharing the same profit rate. While firms who fail do tend to have a meaningful underlying profit rate, the profits of those who succeed tend to grow over time due to reinvestment

time it exits. We use two measures of competitiveness: the firm’s *profitability* (net income/total earning assets) which we observe quarterly, and the firm’s *relative cost*, c_{ij}, which we observe yearly. We perform an unequal variance t-test comparing the profitability (cost) observations for the firm with the profit rate (cost) observations of the surviving firms in the same market. Our null hypothesis is that the firm’s true profitability (cost) is drawn from a distribution with the same mean or higher (lower) as that of surviving firms. We then focus on the p-value of the test to reject this hypotheses, i.e., the likelihood that the firm truly is “competitive” given its performance track-record. Table 4 reports the proportion of firms that reach confidence levels of 90% or more they are not committing Type I errors. Column (1) shows that more than 75% of firms require a 95% probability their true profitability is equal to or better than market mean. Similarly, in column (2) we report that even with a lower hurdle, nearly 65% of firms require 95% confidence their profits are 50% below market mean. Substantial proportions, 53.9% and 44.2%, respectively, exit only after receiving information that makes it less than 0.1% likely they competitive firms. Substantial proportions, 53.7% and 44.2%, respectively, exit only after receiving information that makes it 1% likely that they competitive firms. Column 3 assumes cost rather than profits as the firm's signal. By this measure, firms are far less certain they have avoided Type I error, compared to the results in columns 1 and 2. These estimates likely understate true confidence levels, since firms observe their own cost quarterly, whereas our data are yearly. Nonetheless, it is worth noting that even using this measure, 13.6% of firms require 99% confidence they aren't committing Type I error. Although we are unable to establish what the “optimal” benchmark is using this method, e.g., 90% vs. 99% confidence, and whether the threshold is relative to the mean or absolute levels, this is nonetheless informative. It suggests a substantial proportion of banks exit only after overwhelming evidence they are uncompetitive.

Insert Table 4 about here

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5. Discussion

Exit delays are problematic in numerous contexts and have serious economic consequences. We examine the factors affecting exit timing in a straightforward real-world context: banks. We find noise delays exit relative to a world with perfect information. While this result is anticipated by both rational and behavioral theories, we were able to decompose exit delay into optimal, "suboptimal but rational" and behavioral bias components. We found that most delay in this context is rational, though suboptimal. Firm exit seems to conform to a model of passive learning (efforts to minimize Type I error while detecting their true type), rather than to a model which values the option to cut losses in the future.

Our analysis of the timing of delay relative to two separate rational benchmarks indicates that exit indeed occurs "too late" for a substantial fraction of banks. Eighty-five percent of exit occurs beyond the RL optimum. While failing to employ option logic may not be particularly surprising, what is surprising is that the passive learning threshold firms employ appears to be more stringent than even academic standards. Two-thirds of firms require over 95% confidence their profit is well below the market mean.

The confidence interval itself is suggestive of behavioral bias, but we also found explicit support for behavioral bias. Firms exhibit asymmetric response to profitable periods versus loss periods. Since the rational model treats both equally under the sufficient statistic of cumulative profits, the asymmetry is unanticipated by the rational model. It is however anticipated by escalated commitment through at least three mechanisms: confirmatory bias, attribution bias and motivated reasoning.

We did not find evidence that firms value the option to avoid re-entry costs (Dixit 1989). Exit accelerates with re-entry cost and demand volatility, whereas the options model predicts the opposite. This is not surprising in this context since the opportunity cost (executive wages) likely exceeds the option value of avoiding re-entry costs.

Although we chose this setting because it controlled for a number of factors, it is worth considering how banking differs from other contexts. First, banks require charter approval. This process requires founders have substantial financial capital (approximately $11 million) and high levels of industry specific human capital. Thus entrepreneurs' decisions in this setting may be more rational than in other settings—both because bankers regularly make decisions based on noisy quantitative data and because the financial stakes are larger. Second, banking comprises a large number (approximately 10000) of homogeneous firms, with high frequency (quarterly) and high resolution (2400 variables) public data on the full census of firms. Thus "realized noise" is extremely low relative to other settings. In fact, the efficiency of exit from this setting may stem in large part from data quality. Third, bank regulators participate in exit decisions. Thus the delays exhibited in our data are the better of the entrepreneur's or the regulator's decision rules. This has two implications: 1) the regulators are tolerating substantial exit delay and are themselves subject behavioral bias, 2) the delay we observe is likely shorter than what we would observe in the absence of regulators.

These results have practical implications in addition to their academic implications. First, since both rational and behavioral delays are exacerbated by noise, entrepreneurial losses could be lowered by reducing noise. While we can't reduce fundamental noise, we can reduce "realized noise". One prescription for reducing realized noise is governmental disclosure of census and tax data for all firms. While this ordinarily poses concerns about competition and innovation, the experience in banking suggests these concerns may be overstated.

Second, the same market conditions (cost uncertainty) fueling excess entry (Wu and Knott 2007) also exacerbate delay. Thus markets receiving the lowest benefit per marginal entrant (since there has been so much prior entry) are also the ones with the highest personal cost (entrepreneurial losses). There may be a role for entry regulation in those settings.

Finally, for firm policy, the fact that behavioral biases delay exit beyond the optimum suggests firms could benefit from automated decision rules (Dawes 1971, Dawes et al 1989). This is in fact the goal of Ryan and Lippman (2003). While firms could choose to override the exit rule, having the rule would implicitly make exit the default, rather than the current practice of having continuation as the default. Since substantial exit appears to occur beyond the optimum, this suggests substantial gains to such a practice. Note however our ability to compute optimal exit relies on high resolution quarterly data on the census of banks. Thus the potential benefit from automated decision rules in other settings likely requires public release of economic census data.

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Table 1. Data summary

Observations=226054 firm-periods

Variable	Mean	StDev	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1.Own autocorr (profit t/t-1)	1.135	4.198	-164.091	114.333	1															
2.Market autocorrelation	0.833	0.891	-16.842	2.816	0.008	1														
3.Loss periods/total	0.128	0.218	0.000	1.000	-0.009	-0.043	1													
4.Cumulative profits	24050	172736	-3446443	8775804	0.032	0.018	-0.071	1												
5.p-zero	0.837	0.149	0.333	1.000	0.034	0.302	-0.171	0.053	1											
6.□(own profits)	2161	14090	0	483255	-0.045	0.011	-0.020	0.446	0.008	1										
7.□(own demand)	617	4359	0	159197	-0.070	0.008	-0.003	0.321	-0.008	0.931	1									
8.own cost efficiency	0.201	0.183	0.009	3.972	-0.004	-0.052	0.205	-0.045	-0.195	-0.033	-0.025	1								
9.□(market cost)	0.559	0.107	0.073	1.358	-0.021	-0.043	0.055	0.061	-0.292	0.063	0.062	0.197	1							
10.□(market demand)	0.047	0.034	0.012	3.098	-0.011	-0.077	0.039	0.059	-0.225	0.088	0.091	0.121	0.200	1						
11.mean_wage	2.942	0.104	2.715	3.465	-0.018	0.000	0.088	0.100	-0.344	0.073	0.077	0.094	0.278	0.277	1					
12.Entry cost	-10288	32305	-28795	455994	-0.007	0.016	-0.042	0.129	0.003	0.073	0.091	0.022	0.217	0.284	0.089	1				
13.ln(population)	15.575	0.907	13.025	17.296	-0.007	-0.008	-0.031	0.040	-0.131	0.058	0.051	0.105	0.209	0.057	0.213	0.004	1			
14.ln(market demand)	17.925	0.992	14.449	20.314	-0.009	-0.001	-0.046	0.059	-0.108	0.081	0.080	0.061	0.214	0.148	0.295	0.084	0.957	1		
15.ln(market profit)	12.962	1.147	7.723	16.061	0.001	0.015	-0.114	0.090	0.043	0.074	0.067	0.007	0.171	0.095	0.233	0.182	0.796	0.848	1	
16.ln(market build permits)	10.185	1.190	2.708	12.659	-0.013	0.050	-0.033	0.039	-0.141	0.054	0.044	0.106	0.330	0.074	0.175	0.012	0.886	0.830	0.689	1

Table 2. Comparing expectations of exit models

	Jovanovic	Ryan & Lippman	Dixit	Bias
Own cost (distance from frontier-Knott and Posen(2005))	-	-	-	
Cost dispersion in market j (Knott and Posen(2005))	+	+		
Ex ante probability of being profitable in market j(P_0)		-		
Ex post Profit volatility (s net income t=0 to end)	+	-		
Cumulative profits (sum net income t=0 to t)	+	+		
Outside wage (median banking wage in market j at t)	-	-	-	
Re-entry cost (μ jt (physical + financial assets at entry))			+	
Demand volatility: RMSE from regression:			+	
ln(market output$_t$ /market output $_{t-1}$) = a0 + a1* trend				
Demand growth			+	
Discount rate (year dummies)		-	-	
Bias:				
Intercept		0		+
Negative profits versus positive profits		=		<

Table 3. Results

Accelerated failure time model -weibull distribution
(implicit dependent variable is failure period)

191800 observations, 7720 subjects, 711 failures

	1	2	3	4	5
cost efficiency	**-0.787**	**-0.250**	**-0.754**	**-0.702**	**-0.662**
	0.053	0.018	0.053	0.054	0.048
π(market cost)		**0.163**		**0.638**	
		0.066		0.229	
π(own profits)		**1.53E-05**			
		3.35E-06			
Cumulative profits		**9.85E-07**			
		1.80E-07			
cumulative positive profits				**4.50E-05**	**0.0000467**
				4.67E-06	4.63E-06
cumulative negative profits				**2.84E-06**	**3.24E-06**
				4.27E-07	4.10E-07
P_0 (market)		**0.491**		**1.419**	
		0.044		0.159	
π(market demand)			-0.315		
			0.628		
market growth			**3.414**		
			0.431		
market entry cost			***-1.5E-06***		
			7.52E-07		
mean market wage	**-0.020**	**-0.007**	**-0.016**	**-0.020**	**-0.018**
	0.005	0.002	0.005	0.006	0.005
ln(market population)	**-0.773**	**-0.114**	**-0.419**	**-0.517**	**-0.708**
	0.104	0.030	0.098	0.099	0.098
ln(market demand)	**0.162**	-0.001	0.092	0.069	0.114
	0.078	0.026	0.077	0.084	0.076
ln(market profit)	**0.286**	**0.064**	**0.216**	**0.193**	**0.250**
	0.029	0.007	0.028	0.026	0.027
ln(market building permits)	**0.228**	**0.043**	0.067	**0.192**	**0.232**
	0.035	0.011	0.036	0.038	0.034
Year dummies	yes	yes	yes	yes	yes
Constant	**7.003**	**2.234**	**4.905**	**4.537**	**6.887**
	0.555	0.155	0.515	0.519	0.524
Chi-squared	837.06	1429.65	942.31	1375.81	1253.14
Log-likelihood	-2528.973	-1976.101	-2476.351	-2259.599	-2320.935

Table 4. Probability of Type I error at time of bank exit

	H_0: True Profit Rate of Firm >= Mean Profit Rate of All Survivors in State	H_0: True Profit Rate of Firm >= 50% Mean Profit Rate of All Survivors in State	H_0: Firm Cost <= Mean Cost of All Survivors in State
Pr(Type I error):			
5 – 10%	8.1%	10.2%	6.9%
1 – 5%	20.7%	20.6%	8.9%
0.1 – 1%	22.4%	20.3%	7.6%
< 0.1%	31.3%	23.9%	6.0%
Frequency of Observations	Quarterly	Quarterly	Annual

Note: Profit rate is defined as the Net Income (in Quarter) divided by Total Earning Assets (at end of Quarter)

Figure 1. Exit Decision Nesting

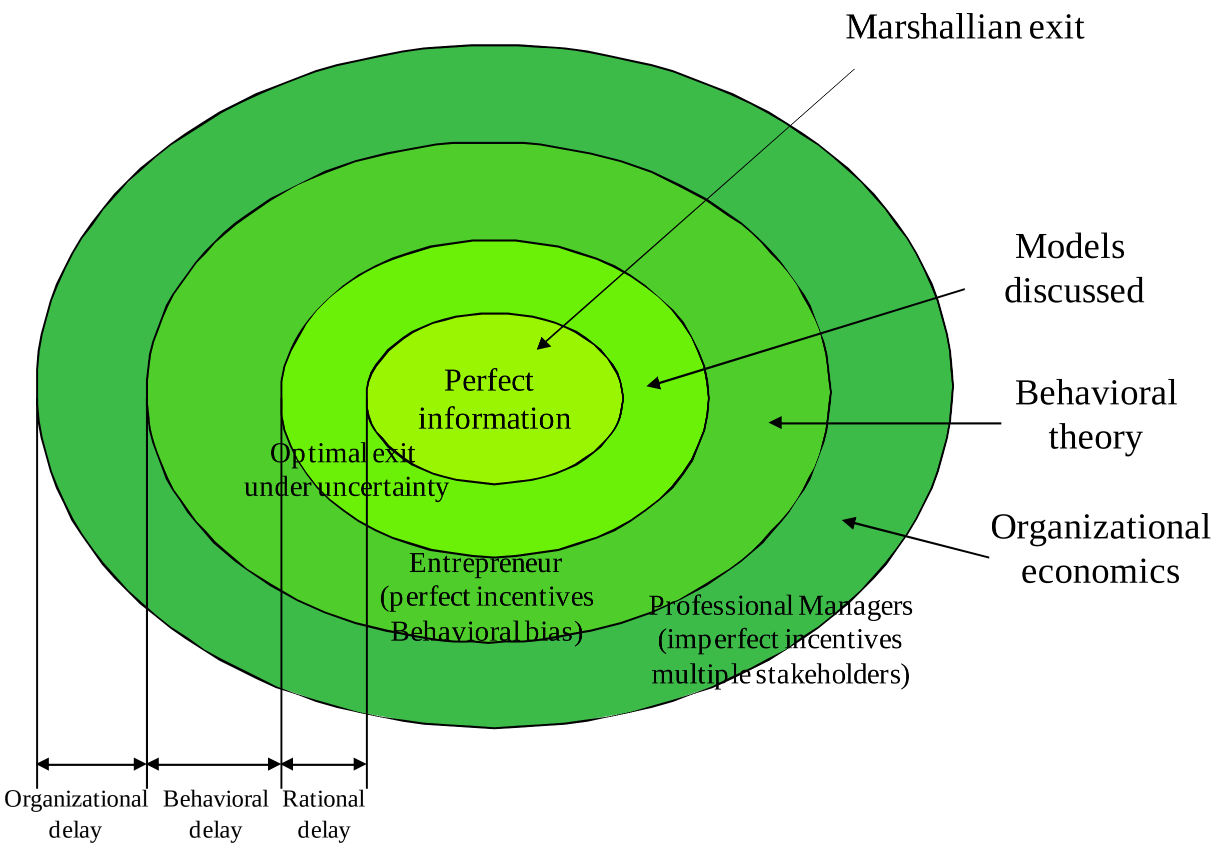

Figure 2. Levels of churn in banking over the period examined

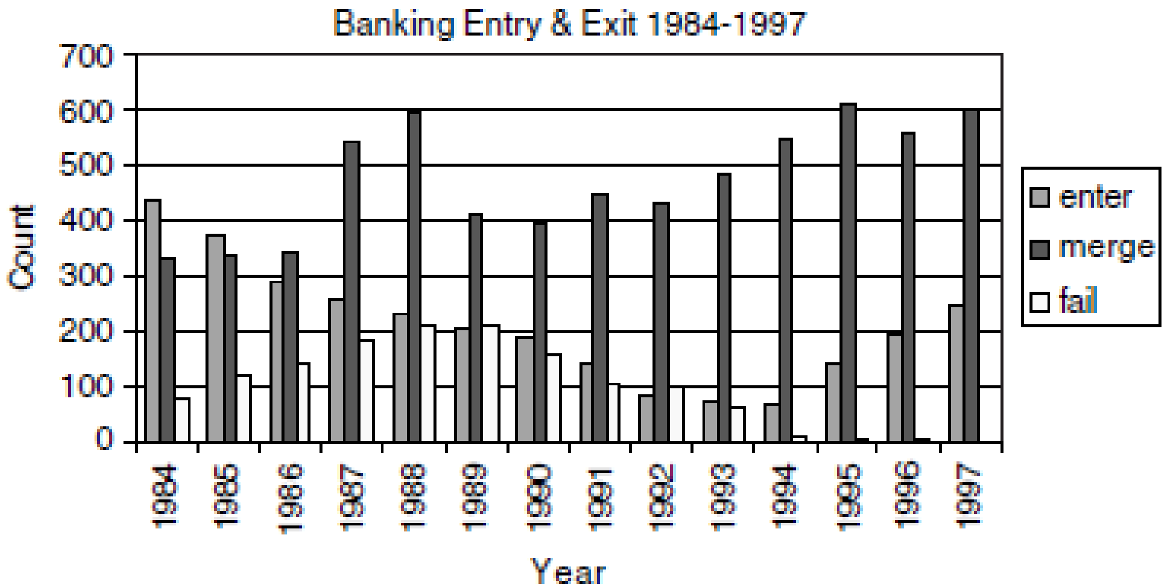

Figure 3. Histogram of periods until failure

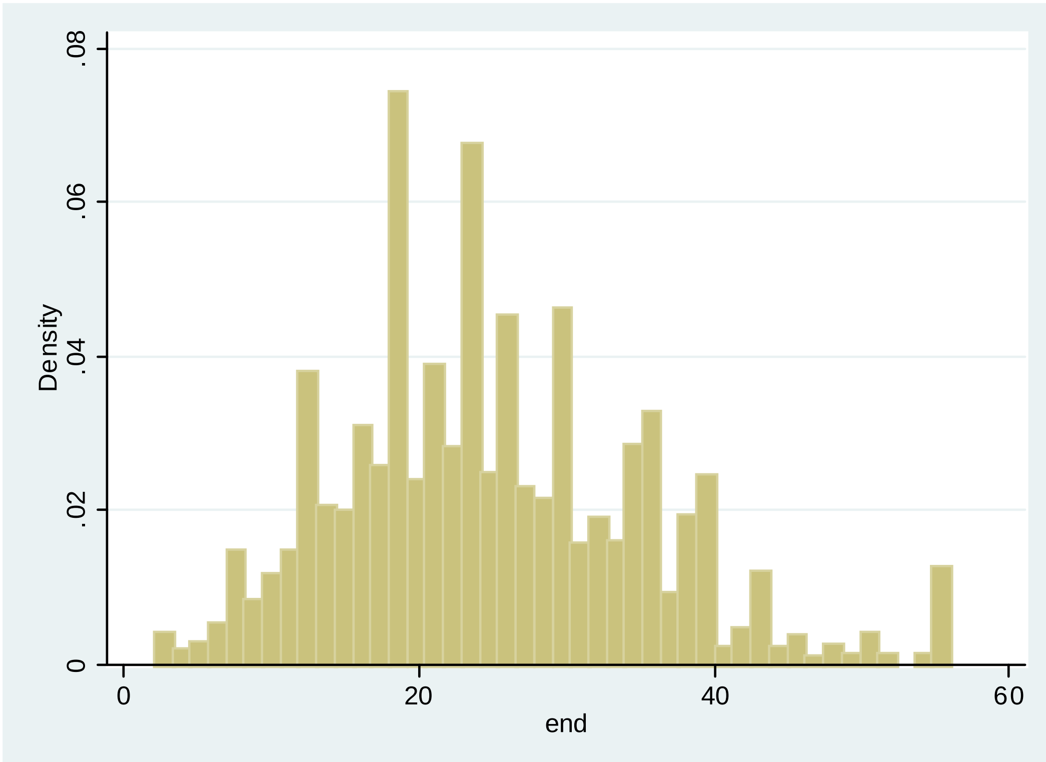

Figure 4. Patterns of consolidation in banking

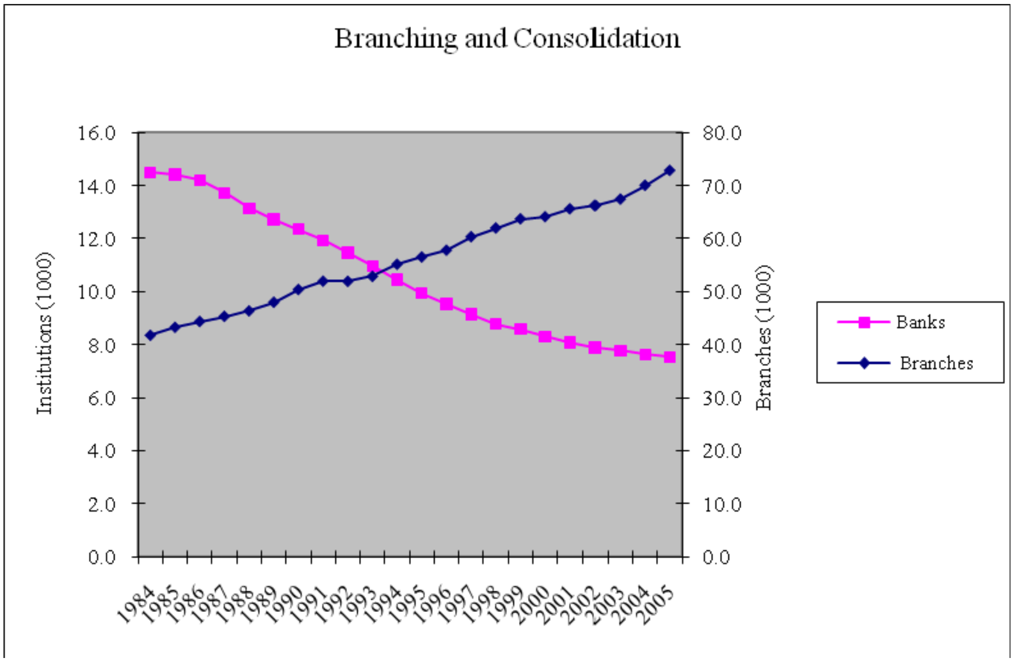

Figure 5. 85% of exit is beyond the Ryan and Lippman optimum