Birth, growth, and life or death of newly chartered banks

Robert DeYoung

Introduction and summary

Thousands of new commercial banks have been chartered in the U.S. over the past two decades. As the U.S. banking industry continues to consolidate, these *de novo* banks are potentially important for preserving competition and providing credit in local markets. However, like other new business ventures, newly chartered banks initially struggle to earn profits, and this financial fragility makes them especially prone to failure. In this article, I document the financial evolution of the typical de novo bank and develop and test a simple theory of why and when new banks fail.

Recent decades have seen an upsurge in the number of mergers and failures among new banks. Figure 1, panel A shows the annual change in the number of commercial bank charters in the U.S. since 1966. Prior to 1980, the reduction in bank charters due to mergers and failures was relatively stable at about 100 charters per year, or about 1 percent of the industry total (figure 1, panel B). The pace accelerated greatly after 1980, and since 1986 about 600 charters, or 5 percent to 6 percent of the industry total, have disappeared each year due to mergers and failures.

To a large extent, this tremendous consolidation can be explained by the repeal of federal and state laws that restricted branch banking and interstate banking. As these restrictions gradually were relaxed, banking companies expanded their geographic reach by acquiring thousands of other banks, and reduced their overhead expenses by converting thousands of affiliate banks into branch offices. This geographic expansion, combined with newly deregulated deposit rates, increased competition between commercial banks just when new information technology was allowing mutual funds, insurance companies, and the commercial paper market to compete for banks' traditional loan and deposit businesses. Under these new competitive conditions, many commercial banks became more vulnerable to economic downturns, and thousands of

banks failed during the 1980s and early 1990s. Over the past two decades, the combined effect of these mergers and failures has reduced the number of commercial banks in the U.S. by nearly 40 percent.

This consolidation has been partially offset by a recurring wave of new bank charters. As shown in figure 1, panel A, over 3,000 de novo commercial banks have been chartered by state and federal banking authorities since 1980. It is generally believed that these newly chartered banks can help restore competition in local markets that have experienced a large amount of consolidation. It is also commonly believed that these newly chartered banks can help replace credit relationships for small businesses whose banks failed or were acquired or reorganized. However, before a newly chartered bank can provide strong competition for established banks and before it can be a dependable source of credit for small businesses, *it must survive long enough to become financially viable*.

I begin by examining the conditions under which investors are likely to start up new banks, including the influence of business cycles, merger activity in local banking markets, and the policies of federal and state chartering authorities. Next, I track the evolution of profits, growth rates, capital levels, asset quality, overhead costs, and funding mix at more than 1,500 commercial banks chartered between 1980 and 1994. These data suggest that newly chartered banks pass through a period of financial fragility during which they are more vulnerable to failure than established

Robert DeYoung is a senior economist and economic advisor at the Federal Reserve Bank of Chicago. The author thanks Iftekhar Hasan and Curt Hunter for their advice; Richard Cahill, Philip Jackson, and participants at a Federal Reserve Bank of Chicago seminar for helpful comments; Eli Brewer and David Marshall for reading an earlier draft of this article; and especially, Nancy Andrews for outstanding data support.
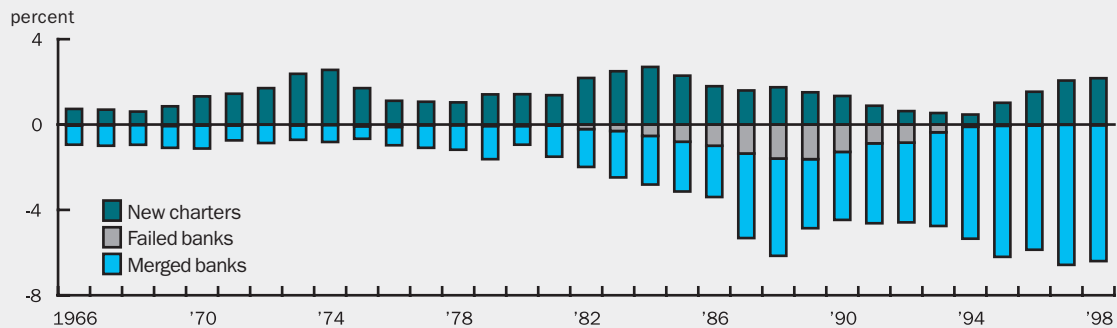
A. Change in number of U.S. commercial bank charters
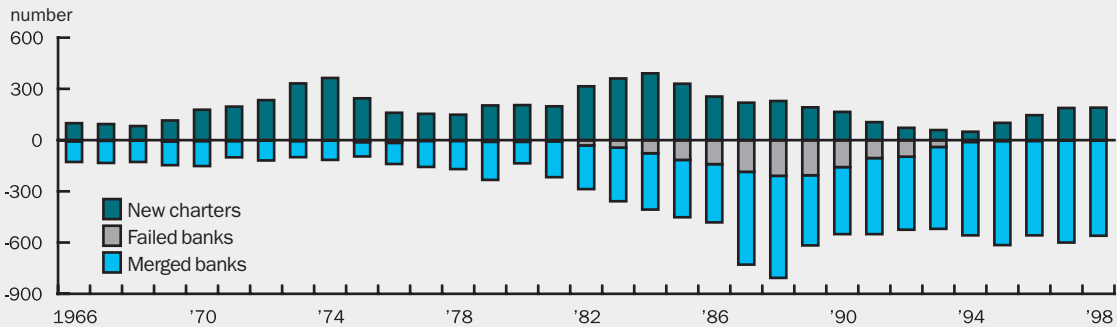
B. Change in number of U.S. commercial bank charters, as a percent of total charters

Source: Federal Deposit Insurance Corporation, 1966–98, "Change in number of insured commercial banks," available on the Internet at www2.fdic.gov/hsob/.

banks. Specifically, new bank capital ratios quickly decline to established bank levels, but new bank profits improve more slowly over time before attaining established bank levels.

Based on these empirical observations, I develop a simple *life-cycle* theory of de novo bank failure, in which the probability of failure at first rises, and then declines with the age of the new bank. I use *hazard function analysis* to test this simple theory for 303 new commercial banks chartered in 1985, just as the wave of bank failures shown in figure 1 was picking up steam. The tests offer support for the simple theory. On average, the results suggest that newly chartered banks are less likely to fail than established banks during the first few years of their lives; however, new banks quickly become substantially more likely to fail than established banks; and, over an extended period of time, new bank failure rates gradually converge to the failure rates of established banks.

What are the implications of these results for bank supervision and bank competition policy? The results suggest that the policies in place during the 1980s successfully insulated new banks from economic

disruptions early in their lives, but were less successful in preventing new banks from failing after the initial years. Clearly, de novo bank failure rates could be reduced by requiring investors to supply higher amounts of start-up capital or by requiring banks to maintain extranormal capital-to-asset ratios in the early years—indeed, the latter policy option was adopted by federal bank supervisors during the 1990s. However, *failure-proofing* de novo banks is not an optimal policy. The social costs of small bank failure are relatively low, and setting higher capital requirements would at some point discourage investment in new banks and thereby limit the competitive benefits of de novo entry.

Birth of new banks

As illustrated in figure 1, panel A, the number of new banks started up each year has ebbed and flowed over the past three decades. There are a number of explanations for these patterns. Like all new business ventures, new banks are more likely to form when business conditions are good. For example, new bank charters bulged to well over 250 per year during the

general economic expansion of the mid-1980s. This high rate of bank start-ups also coincided with the relaxation of unit banking laws in a number of states, laws that had prevented banking companies from operating affiliates in multiple locations. The steady decline in new charters during the late 1980s and early 1990s, which bottomed out at about 50 new banks per year, also had multiple causes. Difficult times in regional banking markets made new bank start-ups unprofitable in many regions (bank failures reached their peak in 1988), and a national recession in the early 1990s reinforced this trend. New bank charters have been on the increase since then, reaching over 100 per year in 1997 and 1998, in large part due to the extended economic expansion of the 1990s.

Conditions in local banking markets also influence bank start-ups. Moore and Skelton (1998) find that there are more de novo banks 1) in markets that are experiencing healthy economic growth, 2) in highly concentrated banking markets in which competition among existing banks is weak, and 3) in markets where small banks are under-represented and, hence, small businesses are not being adequately served. These results imply that new banks will be more likely to start up in local markets where mergers have reduced the number of competing banks, and where the resulting market power has reduced the level of banking services. In such markets, new banks should receive a profitable welcome from customers unhappy with paying high prices for financial services or from businesses whose credit relationships were disrupted when their bank was acquired or failed. Researchers only recently began investigating these phenomena, so there is not yet a consensus on the results. In a study of de novo bank entry in all U.S. markets between 1980 and 1998, Berger, Bonime, Goldberg, and White (1999) find that the probability of de novo entry is higher in local markets that have experienced mergers or acquisitions during the previous three years, particularly mergers and acquisitions involving large banking organizations. In contrast, Seelig and Critchfield (1999) find that local market entry by acquisition deters entry by de novo banks and thrifts.[1] Their results are based on a study of de novo banks and thrifts between 1995 and 1997, a time when banking conditions were exceptional and restrictions on geographic mobility were virtually nonexistent.

Differences in the policies of the legal authorities that grant commercial bank charters can also affect the rate and location of new bank start-ups. A de novo national bank receives its charter from the Office of the Comptroller of the Currency (OCC), while a de novo state bank receives its charter from the banking

commission of the home state. The OCC has historically been more liberal in granting charters than most state authorities. Its policy has been that market forces, not the chartering authority, should determine which local markets need and can support new commercial banks. In contrast, many state chartering authorities have historically applied *convenience and needs* tests when considering applications for new bank charters, denying applications if they judge that the convenience and needs of the banking public are already adequately served. Although this federal–state difference in chartering philosophy has diminished over time, DeYoung and Hasan (1998) find that national banks were chartered with greater frequency than state banks during the 1980s and early 1990s, and that the financial performance of de novo national banks initially lagged that of de novo state chartered banks.[2] This suggests that national banks chartered during the 1980s were likely to have had a higher probability of failure than newly chartered state banks operating under similar economic and market conditions.

A concern shared by all chartering authorities is that newly chartered banks start out with enough equity capital to survive through the several years of negative earnings and rapid asset growth that is typical of de novo banks. The dollar amount of start-up financial capital required for approval might be $3 million, $10 million, or even as much as $20 million, depending on the proposed location and business plan of the prospective bank. Larger amounts of start-up capital are generally required for urban banks, for banks locating in vibrant economic markets, and for banks with business strategies that feature fast growth (for example, a new Internet bank).

Once a new bank opens its doors for business, regulatory scrutiny shifts from the applications staff to the examination staff. Bank supervisors pay closer attention to newly chartered banks than to similarly situated established banks, although the difference in treatment varies depending on the new bank's primary regulator. Federal Reserve supervisors will conduct full scope examinations for safety and soundness at a newly chartered bank at six-month intervals (established banks are examined every 12 to 18 months) and will continue to schedule exams at this frequency until the bank receives a strong composite CAMEL rating (that is, a rating of 1 or 2) in two consecutive exams. The Federal Deposit Insurance Corporation requires that all newly chartered state and national banks maintain an 8 percent tier 1 equity capital-to-risk-based assets ratio for their first three years of operation, while the Federal Reserve requires new state chartered Fed member banks to hold this ratio above

9 percent for three years. These temporary extranormal capital requirements for new banks (the tier 1 requirement for established banks to be considered *adequately capitalized* is only 4 percent) are a relatively recent supervisory response to de novo failure experience of the 1980s. Bank supervisors also prohibit new banks from paying out dividends for several years and, in some cases, require new banks to maintain minimum levels of loan loss reserves.

Evolution of new banks

Relatively few research studies have examined how banks grow and evolve in the years immediately after they receive their charters.[3] Brislin and Santomero (1991) show that the financial statements of a new bank can fluctuate rapidly and dramatically during its first year. A handful of studies have examined how the profitability of de novo banks grows over time (for example, Hunter and Srinivasan, 1990, and DeYoung and Hasan, 1998). Another strand of research documents how small business lending becomes less important to de novo banks as they mature (for example, DeYoung, Goldberg, and White, 1999). In this section, I analyze how a broad group of de novo bank characteristics not typically considered in the literature evolve over time, including de novo bank profits, growth rates, capital ratios, sources of income, financing mix, overhead ratios, and loan quality.

Each of the eight panels in figure 2 examines a different financial ratio and compares its average value for a sample of de novo commercial banks to its average value for a sample of established commercial banks. The de novo bank sample includes 4,305 observations of commercial banks that were chartered between 1980 and 1994, were between one and 14 years old when they were observed, and were located in urban banking markets. The established bank sample includes 4,305 observations of commercial banks that were at least 14 years old when they were observed, operated in urban banking markets, and were similar to the de novo banks in terms of asset size. These two samples of banks were originally constructed by DeYoung and Hasan (1998). Box 1 contains additional details about the two bank samples.

To construct each of the graphs in figure 2, I divided the de novo banks into 14 separate age groups (one-year old banks, two-year old banks, etc.). I then calculated the median average for the financial ratio in question—say, return on assets (ROA)—for each age group. Plotting these 14 average values in chronological order creates a *time path* showing how ROA evolves as the typical de novo bank matures. Finally, I superimposed the value of ROA at the 25th, 50th,

and 75th percentiles of the established bank sample as horizontal lines over the de novo bank time path. These horizontal lines serve as *maturity benchmarks* against which to compare the progress of de novo banks over time. The rate at which the de novo time path converges with the maturity benchmarks indicates the speed at which the de novo banks mature.

While each of the individual graphs in figure 2 has a straightforward interpretation when considered in isolation, these eight panels reveal a richer story when they are interpreted in conjunction with each other. For example, by itself the return on assets (ROA) graph (panel A) merely confirms the results of existing studies of de novo bank profitability, that is, that the typical new bank loses money until it is about 18 months old and continues to underperform the average established bank for about a decade. But when the ROA graph is considered together with the asset-growth (panel B) and equity-to-asset (panel C) graphs, a simple theory of de novo failure begins to emerge. De novo banks average an extraordinary 20 percent annual rate of growth during the first three years of their lives. While this fast growth rate is increasing the amount of assets against which new banks need to hold equity capital, the losses suffered during the first and second years of these banks' lives are depleting their equity capital. Despite initially high capital levels, the equity-to-asset ratio of the typical new bank declines very quickly, entering the established bank range after just three years. Thus, panels A, B, and C suggest the probability of failure should increase as new banks pass their third year of life— their capital has declined to established bank levels by year three, but their asset growth and profitability do not converge with those of established banks until at least year ten.

The remaining five panels in figure 2 are consistent with the simple theory of de novo bank failure suggested by the ROA, asset growth, and equity-to-asset panels. For example, newly chartered banks initially have almost no nonperforming loans (panel D). This is because these banks' loan portfolios are composed disproportionately of *unseasoned* loans made recently to borrowers who demonstrated strong financial fundamentals. However, as time passes some of these new borrowers will naturally run into trouble, and the quality of de novo banks' loan portfolios will naturally decline. This happens quite quickly for the typical de novo bank, as its level of nonperforming loans rises slightly above the median level for established banks after three years—just as de novo banks are depleting their excess capital cushions and well before new bank profitability rates have matured.
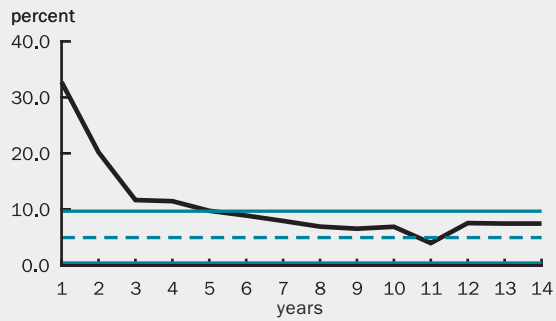
FIGURE 2

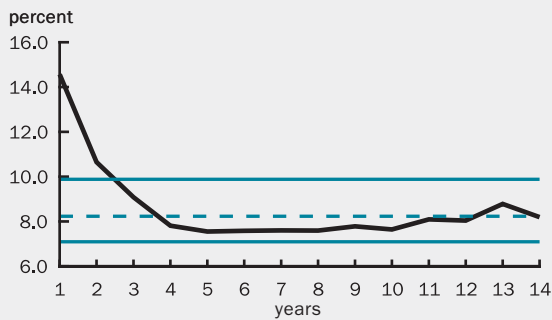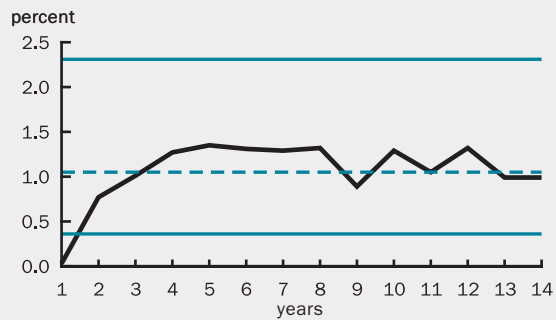**Financial ratio time paths for de novo banks**

A. Return on assets

percent
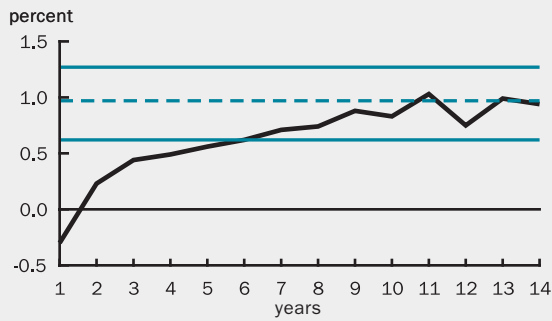
B. Annual asset-growth rate

percent

C. Equity-to-asset ratio

percent

D. Ratio of nonperforming banks

percent

E. Ratio of interest-bearing assets
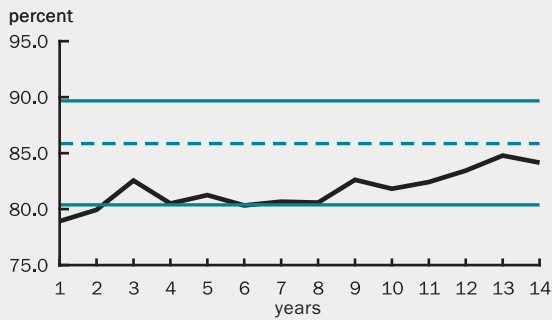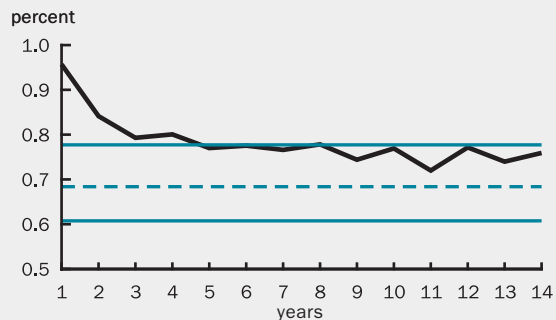
percent

F. Fee income ratio
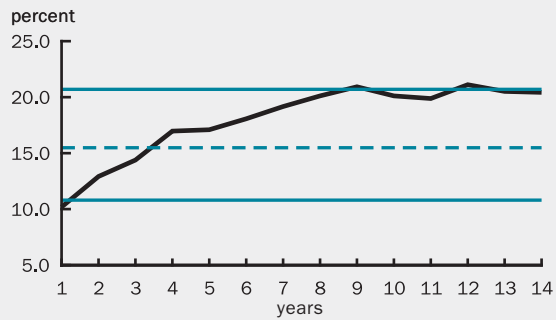
percent

G. Ratio of large deposits
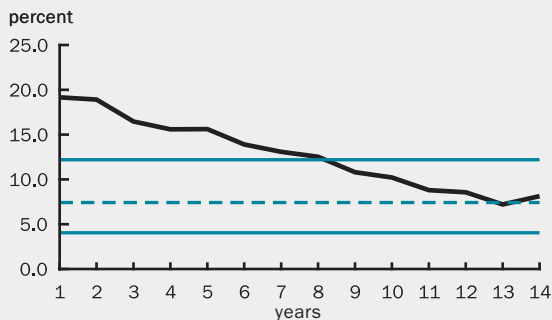
percent

H. Accounting efficiency ratio

percent

Notes: The data are described in box 1. The three colored horizontal bands are maturity benchmarks that indicate the twenty-fifth, fiftieth, and seventy-fifth percentiles of the distribution of the ratio in question for the established bank sample. The black line plots the median value of the ratio in question for the banks of various ages in the de novo bank sample. Return on assets is net income divided by total assets. Annual asset-growth rate is the percent increase in total assets over the previous year-end total. Equity-to-asset ratio is the book value of equity divided by total assets. Ratio of nonperforming loans is loans past due 90 or more days plus nonaccruing loans divided by total loans. Ratio of interest-bearing assets is total performing loans plus total securities divided by total assets. Fee income ratio is noninterest income divided by net interest income plus noninterest income. Ratio of large deposits is deposits in accounts greater than $100,000 divided by total deposits. Accounting efficiency ratio is noninterest expense divided by net interest income plus noninterest income.

Source: National Information Center, 1988, 1990, 1992, and 1994, "Report of income and condition," selected banks, December 31.

The slow rate at which de novo bank profitability improves appears to be attributable more to cost factors than to revenue factors. Although the percentage of de novo bank assets invested in interest-bearing assets, such as loans and securities, starts out relatively low and increases only slowly over time (panel E), the typical de novo bank outperforms one-quarter of the established banks in this area after only three years. (De novo bank ROA does not reach the 25th percentile benchmark until year six.) Even more impressive is the speed at which new banks develop the ability to generate fee income (panel F). The typical de novo bank outstrips the average established bank in fee-based revenues after only three years, and outperforms three-quarters of the older banks in this area after about nine years. By virtue of their newness, de novo banks may be less constrained by the inertia of existing customer relationships and existing employee habits and, therefore, may be better able to impose fees on retail customers or to enter into less traditional

Both the de novo bank sample and the established bank sample were taken from a primary data set used originally in a study by DeYoung and Hasan (1998). For the current study, I added variables from the "Reports of income and condition" (call reports). The primary dataset is an unbalanced panel consisting of 16,282 observations of 5,435 small, urban commercial banks at year-end 1988, 1990, 1992, and 1994. Not all of the banks are present in each of the four years because some banks failed, were acquired, or received their charters during the sample period. There are 2,611 banks present in all four years, 977 banks in three of the four years, 1,005 banks in two years only, and 842 banks in just one year.

Banks had to meet a number of conditions to be included in the primary dataset. First, banks had to have less than $500 million of assets (in 1994 dollars). By definition, newly chartered banks are small, and established banks that are large will not serve as good benchmarks against which to judge the progress of young banks. Large banks have access to production methods, risk strategies, distribution channels, and managerial talent not available to small banks. Second, all banks had to be headquartered in metropolitan statistical areas (MSAs). Demand for banking products, as well as competitive rivalry among banks, can be quite different in rural and urban markets, and may cause young banks to develop differently in these two environments. Third, banks had to be at least 12 months old at the time of observation. For example, a bank that was chartered during 1993, but was observed at year-end 1994, is referred to as a one-year old bank. Brislin and Santomero (1991) find that financial statements are quite volatile during the first year of a bank's operations, which makes performance difficult to measure. Fourth, all banks had to make loans *and* take deposits, eliminating special purpose banks such as credit card banks. Fifth, banks that were 14 years old or less (that is,

banks that would be in the de novo sample) were excluded if they held more than $50 million in assets at the end of their first year. This filter prevents established banks that received new charters as part of regulatory reorganizations and established thrift institutions converting to bank charters from being identified as de novo banks.

The resulting de novo sample comprises 4,305 observations of 1,579 different banks 14 years old or younger. Roughly 47 percent of these de novo banks hold federal charters and roughly 21 percent are affiliates in multibank holding companies. The established bank sample was constructed by choosing 4,305 observations of 1,514 different banks, each more than 14 years old, from the primary dataset. Roughly 25 percent of these established banks hold federal charters and roughly 27 percent are affiliates in multibank holding companies. The established banks were chosen to have roughly the same asset-size distribution as the de novo bank sample, as follows: Banks more than 14 years old were grouped into ten asset categories ($0–$50 million, $50–$100 million, ..., $450–$500 million). Established banks were drawn at random from each of these size categories, depending on the number of de novo banks of each asset size. The assets of the resulting established bank sample average $55.97 million with a standard deviation of $49.64 million, compared with the de novo bank sample average of $54.39 million and standard deviation of $48.70 million.

Obviously, there is no bright line that separates de novo banks from established banks. I chose the 14-year old threshold for two reasons. First, it is the maximum age at which previous studies refer to commercial banks as de novo (see Huyser, 1986, and DeYoung and Hasan, 1998). Second, choosing a relatively large number for this threshold ensures that the maturity benchmarks in figure 2 contain only banks that are fully mature.

fee-generating lines of business. In addition, de novo banks tend to start up in markets where business conditions are strong, and selling fee-based financial services may be easier in these markets.

In contrast to their reasonably strong ability to generate revenue, newly chartered banks have a difficult time controlling expenses. De novo banks initially use large deposits twice as intensively as do established banks, and this disparity only slowly disappears (panel G). This suggests that de novo banks tend to finance their fast asset growth by purchasing funds rather than by growing their core deposit base. All else being equal, this is an expensive and potentially risky financing strategy, because large depositors are more sensitive to changes in interest rates than are retail depositors and require higher rates to leave their funds in the bank. The accounting efficiency ratio graph (panel H) indicates that newly chartered banks also have relatively high levels of overhead expenses (for example, branch locations, labor expenses, and computer equipment) and that these fixed factors of production are not used at near full capacity for a number of years. Excess overhead capacity not only depresses bank profitability but, by increasing operating leverage, it makes bank profits more sensitive to fluctuations in bank revenues.

Note that each of the panels in figure 2 exhibits what is known as *survivor bias*, because some de novo banks fail before they are 14 years old. For example, average de novo ROA equals approximately 0.4 percent for the three-year old banks, which is about twice as large as the average ROA of 0.2 percent for the two-year old banks. For the most part, this substantial improvement can be attributed to better performance as young banks grow older and larger. But some amount of this improvement occurs because some of the most unprofitable de novo banks failed between years two and three and dropped out of the sample. Although this second explanation is responsible for only a small amount of the large increase in ROA (as we shall see, very few de novo banks fail after only two years of operation), it is a good illustration of how survivor bias can affect our results. Thus, the most exact way to interpret the ROA time path is as follows: If a newly chartered bank survives to be three years old, one would expect its ROA to be about 0.4 percent. I revisit the issue of survivor bias when I estimate time to failure models in a later section (see Estimating hazard functions section, starting on page 26).

Hypothetical hazard rates

The time paths in figure 2 imply that de novo banks will at first be very unlikely to fail, perhaps even less

likely to fail than established banks. Despite the losses typically incurred during their first year of operation, de novo banks initially have very high cushions of equity capital and very low levels of nonperforming loans. But the time paths in figure 2 also imply that de novo banks become dramatically more likely to fail as time passes, and quickly may become more likely to fail than established banks. As de novo banks age, their initially high capital cushions and low nonperforming loan ratios move rapidly toward established bank levels—much more rapidly than their profitability reaches established bank levels.

The combined effect of these financial ratio time paths on the timing and probability of de novo bank failure is suggested by the hypothetical *hazard functions* in figure 3. A hazard function tracks changes over time in the *hazard rate*, which is simply the probability that a bank will fail at a particular time, given that it has survived through all of the previous periods leading up to that time.[4] The horizontal line at P* represents the hypothetical hazard rate for established banks, and the curved line plots the hypothetical hazard rate for newly chartered banks. Although this figure is highly stylized, the relative shapes of the two functions are consistent with the combined financial ratio time paths shown in figure 2.

The constant, non-zero hazard rate depicted in figure 3 for established banks is an obvious simplification. Historically, established banks are more prone to failure during recessionary periods, and almost completely unlikely to fail during expansionary periods. This simplification focuses attention on the issue of primary interest here, the failure rate of newly chartered banks *relative to* the failure rate of established banks.

The hypothetical hazard rate for newly chartered banks starts out at zero in figure 3, which makes sense because these banks are so heavily capitalized at the outset. But, as we saw in figure 2, de novo bank capital

FIGURE 3

Hypothetical probabilities of failure
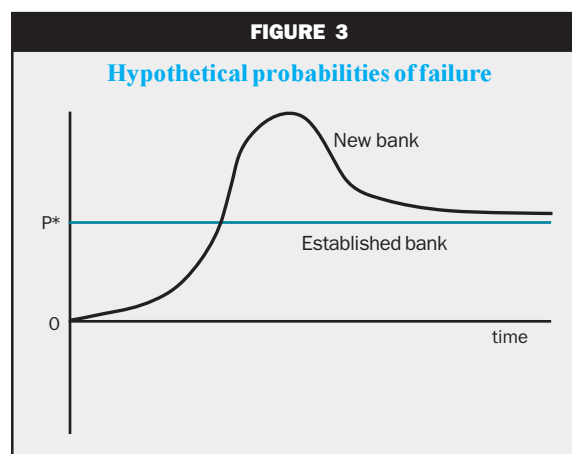
ratios decline to established bank averages after about three years, while de novo bank profits, asset quality, and growth rates do not reach (or return to) established bank levels for around ten years. When these time paths are considered simultaneously, they imply the hypothetical patterns displayed in figure 3. The hypothetical hazard rate for new banks increases at first (for example, between ages one and three) as new banks become increasingly vulnerable to economic fluctuations; it exceeds the established bank hazard rate for a time (for example, after year three); and it eventually declines to converge with established bank levels (for example, around year ten). Regardless of the exact shape and timing of the de novo bank hazard function, it must eventually converge with the established bank hazard function, because by definition new banks that survive eventually turn into established banks.

A rough way to check the relative accuracy of the hypothetical hazard functions drawn in figure 3 is to calculate *Z-score probabilities of failure* for de novo banks and established banks. The Z-scores are constructed as follows:

$$Z = \frac{ROA \;+\; equity\,/\,assets}{standard\ deviation\ of\ ROA}.$$

The Z-score indicates the number of standard deviations that ROA would have to fall below its average value in order to wipe out 100 percent of the bank's equity capital. For example, if a bank has 5 percent equity capital and, on average, it earns ROA of 1 percent with a standard deviation of 1 percent, then its Z-score would equal 6.00. In this case, the bank's ROA would have to decline by 6 standard deviations below its average (to –5 percent) for its losses to exhaust its capital cushion. Thus, the higher a bank's Z-score, the lower its probability of failure. Z will increase (that is, the probability of failure will decrease) with higher levels of average ROA; Z will increase with higher levels of equity to assets; and Z will increase with lower variability in ROA.[5]

Table 1 displays Z-scores for the established bank sample, for the de novo bank sample, and for several subsamples of de novo banks. All of these calculations employ the data used to construct the graphs in figure 2. For each sample or subsample of banks, Z is calculated using the median average of *ROA*, the mean average of *equity/assets*, and the cross-sectional standard deviation of *ROA*. (I use the median *ROA* because the mean *ROA* is skewed downward by banks that incurred large losses.) Because these Z-scores are averages, they represent the likelihood of failure for the typical bank in each sample.

In general, the calculations shown in table 1 suggest that becoming insolvent is a relatively unlikely event for the typical bank in these samples. For example, the lowest Z-score (highest probability of insolvency) is 3.01, or about 3 standard deviations, for the average three- to five-year old bank. Assuming that Z is normally distributed, this implies only a 13 in 1,000 (0.13 percent) chance of becoming insolvent. Given the large number of bank failures during the sample period (see figure 1, panel A), the *level* of the failure

TABLE 1					
Average Z-scores					
		Components of average Z-score			
	Number of banks	**Median ROA**	**Mean capital-to-assets ratio**	**Cross-sectional standard deviation of ROA**	**Average Z-score**
De novo banks					
1 to 14 years old	4,305	.0057	.0957	.0230	3.97
Less than 3 years old	667	.0006	.1231	.0206	6.00
3 to 5 years old	1,424	.0050	.0814	.0287	3.01
6 to 10 years old	1,570	.0074	.0762	.0195	4.28
11 to 14 years old	644	.0089	.0795	.0155	5.70
Established banks					
More than 14 years old	4,305	.0097	.0867	.0129	7.48

Notes: Z-scores were calculated using formula described in the text and data described in box 1. The selected commercial banks are also described in box 1.
Source: Author's calculations based on year-end data from the National Information Center, 1988, 1990, 1992, and 1994, "Report of income and condition," selected banks.

probabilities implied by these Z-scores is probably too low.[6] However, these Z-scores are still useful, because they summarize the information in figure 2 into a single number that *ranks* the probability of failure across banks of different ages.

Overall, the analysis suggests that newly chartered banks are more likely to fail than established banks: The average de novo Z-score of 3.97 is considerably smaller than the average established bank Z-score of 7.48. On average, de novo banks and established banks have nearly identical capital-to-asset ratios, so any difference in their implied failure rates must be due to the level and variability of ROA. Indeed, the median de novo bank ROA is only about half as large as the median established bank ROA (.0057 versus .0097), and ROA is nearly twice as variable across the de novo banks than across the established banks (.0230 versus .0129).

Analyzing the Z-scores across de novo banks of different ages provides some support for the shape of the de novo bank hazard function in figure 3. The implied probability of failure is relatively low for banks less than three years old ($Z = 6.00$); is substantially higher for three- to five-year old banks ($Z = 3.01$); and then gradually declines toward established bank levels for banks that survive beyond five years ($Z = 4.28$) and beyond ten years ($Z = 5.70$). Looking at the components of these average Z-scores reveals why the probability of failure changes as new banks mature. The youngest group of de novo banks are the least likely to fail because their earnings are relatively stable (although they average near zero) and their capital cushions are large. The three- to five-year old de novo banks are more likely to fail because, although they have higher average earnings, their capital cushions have been depleted and their earnings are highly variable. Once banks are five to ten years old, increasing earnings, increasing capital, and declining earnings volatility all contribute to a reduced probability of bank failure.

Estimating hazard functions

Next, I test whether the hypothetical hazard functions in figure 3 accurately depict the relative rates at which newly chartered banks and established banks fail. The Z-score analysis discussed above provides some support for these hypothetical hazard functions, but that evidence is crude at best and suffers from survivor bias in the data. In this section, I employ more sophisticated techniques to estimate hazard functions for both newly chartered and established banks. These techniques explicitly account for survivor

bias caused by failures and acquisitions during the sample period. In addition, these techniques generate continuous (or nearly continuous) hazard functions that can be plotted against time, making them easy to compare with the shape of the hypothetical hazard functions in figure 3. Finally, one of these techniques tests whether differences in de novo and established bank failure rates are caused by differences in these banks' locational, regulatory, or organizational characteristics.

Data on bank failures

Table 2 displays some summary statistics for a bank failure dataset Federal Reserve Bank of Chicago staff created for the purpose of this study. This dataset contains 56 quarters of information on 2,653 banks from 1985 through 1998, and is constructed from the "Reports of income and condition" (call reports) and from the failures, transformations, and attributes tables in the National Information Center database. The dataset includes 303 newly chartered commercial banks that opened their doors during 1985 and 2,350 established commercial banks that had been in operation for at least 25 years in 1985. The established banks each had less than $25 million in assets (1985 dollars); had equity capital equal to at least 5 percent of their assets; and were located in states in which at least four de novo banks started up in 1985. The dataset tracks each of these 2,653 banks across time and records the quarters in which banks left the dataset because they either failed or were acquired by another bank.

These data cover a period during which there were economic disruptions of sufficient magnitude to cause a statistically meaningful number of bank failures. Commercial bank failures were extremely rare in the U.S. during the 1950s, 1960s, and 1970s, due to generally good economic times, regulatory limits on the risks that banks could take, and legal entry barriers that protected banks from competition. But the combination of banking deregulation and volatile interest rates during the 1970s and 1980s exposed banks to greater risks and more competition. As seen in figure 1, panel A, bank failures accelerated from near zero in 1980 to over 100 failures per year from the mid-1980s through the early 1990s. The catalyst for these bank failures was a series of substantial economic disruptions, including a general recession in the early 1990s and a number of regional recessions in the mid- to late 1980s, the most disruptive of which was due to land price deflations in Texas and other oil-producing states.

For the purposes of this article, I consider a bank to have failed when at least one of the following

characteristics affect the probability of bank failure.

Nonparametric hazard functions

I use the bank failure data, summarized in table 2, to estimate separate hazard functions for newly chartered banks and established banks, and then compare these estimated hazard functions with the hypothetical hazard functions in figure 3. I employ two different hazard function techniques to produce these estimates—a *nonparametric*, or *actuarial*, approach, and a *parametric*, or *duration model*, approach.

An actuarial hazard function is simply a series of actuarial hazard rates strung together in chronological order. Calculating the actuarial hazard rates is straightforward and intuitive. For example, to calculate the 1990 hazard rate for a set of banks that were chartered in 1985, one simply divides the number of these banks that failed during 1990 by the number of the banks that still existed at the beginning of 1990. Thus, the hazard rate tells us the probability of failure in 1990 conditional on having survived for five years. The following, more exact, formula can be used to calculate the actuarial hazard rate for any time period, T:

occurs: 1) the bank is declared insolvent by its regulator; 2) the bank receives regulatory assistance (for example, a capital injection) without which it would become insolvent; or 3) the bank is acquired soon after its net worth has declined to less than 1 percent of assets. In terms of raw percentages, 16.5 percent of the de novo banks failed before the end of the 14-year sample period. While this is over twice the 7.9 percent failure rate for the established banks in the sample, it is well below the reported failure rates for new (nonbank) business ventures. (See box 2 for a short discussion of new bank failures versus new business failures.)

Both the sample de novo banks and the sample established banks were more likely to be acquired than to fail during the sample period. The new banks were more likely to hold state charters; to be located in urban areas; to be located in the Southwest (primarily Texas, but also Louisiana and Oklahoma); and to be affiliates in multibank holding companies. Some of the hazard functions I estimate below include tests of whether these locational, organizational, and regulatory

$$hazard(T) = \frac{\text{no. of bank failures during } T}{\text{no. of banks surviving at start of } T}$$

$$\approx \frac{f(T)}{n(t=0) - \sum_{t=0}^{T-1}\left(f(t)+m(t)\right) - \frac{1}{2}m(T)},$$

where $n(t = 0)$ is the number of banks present at the beginning of the analysis; $f(t)$ represents the number of these banks that failed during time period t; $m(t)$ represents the number of these banks that were acquired in mergers during time period t, and T indicates the current time period. Note the subtle adjustment to the denominator in the second line of this formula: The denominator is reduced by one-half the number of banks that were acquired during the current time period. These banks clearly did not survive until the end of time period T, and subtracting some portion of these banks from the denominator acknowledges the possibility that they might have failed during time T

During the 14 years covered by the bank failure dataset (see table 2), 16.5 percent of the newly chartered banks failed, compared with only 7.9 percent of the established banks of comparable size and location. To put these new bank failure rates into perspective, note that a 16.5 percent failure rate over 14 years is substantially lower than the failure rates typically reported for business start-ups in general. Raw data reported by the U.S. Small Business Administration (1992) suggest that at least 60 percent of new business ventures with less than 500 employees that started in 1977–78 failed within six years. Kirchhoff (1994, pp. 153–169) argues convincingly that these raw data overstate the new business failure rate because, among other things, the data in many instances define firms that changed owners or voluntarily shut down as having failed. After adjusting for these and other

factors, Kirchhoff concludes that, in a best case scenario, 18 percent of new business ventures fail within eight years of start-up—about the same rate of failure as the de novo banks but in half the number of years. Furthermore, the 16.5 percent failure rate for new banks occurred during the worst period of bank failures since the Great Depression.

It should not be surprising that new banks have a better rate of survival than other new businesses. Both federal and state bank regulators deny charters to applicants with questionable financial credentials, restrict business activities, require high amounts of capital, apply regular scrutiny via on-site exams, and have the power to revoke bank charters. Banking start-ups face more severe entry barriers and ongoing scrutiny than new businesses in most other industries, and this *selection bias* naturally leads to a higher survival for new banks.

had they not been acquired. Although weighting these banks by one-half is a crude and *ad hoc* adjustment, it is important to make some kind of adjustment because, as shown in table 2, acquired banks greatly outnumbered failed banks between 1985 and 1998.

I use the above formula to calculate 14 separate hazard rates (one rate for each of the 14 years from 1985 through 1998) for the 303 newly chartered banks. I repeat this exercise for the 2,350 established banks. Plotting the resulting hazard rates in chronological order generates two nonparametric hazard functions, which are displayed in figure 4.

In general, the nonparametric hazard functions in figure 4 resemble the hypothetical hazard functions posited in figure 3. The hazard rate for newly chartered banks is initially zero, and it remains below the established bank hazard rate for several years. As discussed above, this is most likely because the typical new bank holds a healthy equity cushion at the outset. After year three, the new bank hazard rate exceeds the established bank hazard rate, and it remains substantially higher than the established bank hazard rate until year eight. The hazard rate for newly chartered banks peaks in years five, six, and seven at about 1.2 percent—that is, if a newly chartered bank reaches the beginning of any of these years without failing or being acquired, it has about a 1.2 percent chance of failing before the year is out. At this point, the typical new bank's capital ratio has declined to established bank levels, but its profitability has not

yet attained the level or degree of stability found at established banks. After year eight, the new bank hazard rate approaches the established bank hazard rate from above, suggesting that the maturation of new banks is well under way at this point.

The results displayed in figure 4 are consistent with the simple life-cycle theory of de novo bank failure. The nonparametric techniques used to generate figure 4 paint a good general picture of the rate at which new banks fail *relative to* established banks. But these nonparametric techniques do not control for the survivor bias in the data and, as a result, they understate the hazard rate at any given point in time.

FIGURE 4

Nonparametric hazard rates
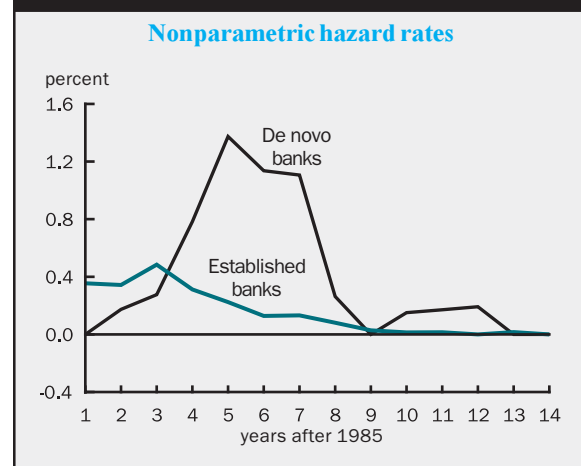
Furthermore, these techniques are not useful for testing how much, if any, of the difference between the new bank and established bank failure rates is caused by the economic, regulatory, and organizational conditions under which newly chartered banks operate. In the final step in this analysis, I use econometric *duration analysis* to estimate hazard functions. These parametric methods account for survivor bias and control for environmental conditions that can affect the probability of failure.

Parametric hazard functions

Duration analysis is a statistical regression approach. The dependent variable in these regressions is t, the length of time that passes between a new bank's start-up date and its subsequent failure. For established banks, t is the length of time between its first observation in the dataset (in this case, the first quarter of 1985) and its subsequent failure. The period measured by t is often referred to as a bank's *duration*. Because the banks in this dataset are observed quarterly, duration will range from $t = 1$ for banks that fail during the quarter in which they begin operations, to $t = 56$ for banks that fail in the fourth quarter of 1998.

The simplest duration approach includes no explanatory variables. The analyst starts by selecting a probability distribution formula that has a shape that is roughly similar to the actual distribution of the duration variable t, and uses maximum likelihood techniques to estimate parameter values that shape that probability distribution formula more exactly to the actual duration data. Here, I use a *log-logistic* distribution formula, because this is capable of producing hazard functions that have shapes similar to the hazard functions in figures 3 and 4. (Details of these duration model procedures can be found in the appendix to this article or in Greene, 1997). Once the parameters of the distribution formula have been estimated, they can be used to construct hazard functions as follows:

$$hazard(T) = \frac{f(T)}{1 - F(T)},$$

where $f(T)$ is the probability that a bank fails at time T (that is, the log-logistic probability density) and $F(T)$ is the probability that a bank fails before time T (that is, the log-logistic cumulative probability distribution). The denominator, $1 - F(T)$, is the log-logistic *survival function*, which is the probability that a bank neither fails nor is acquired before time T. This parametric hazard function has the same general interpretation as the nonparametric hazard function calculated in the previous section—they are both estimates of the

probability that a bank will fail at time T given that it has survived until time T. One difference is that the hazard function generated by this parametric approach will be a smooth and continuous function of time similar to the hypothetical hazard functions in figure 3, as opposed to the segmented nonparametric hazard function in figure 4.

The duration models I estimate here control for survivor problems in the data. Recall that many of the sample banks either survived beyond the end of the sample period or were acquired during the sample period. These banks are known as *censored observations*. We cannot assign a duration value t to these banks because we cannot observe their ultimate fate (failure or survival). Furthermore, history suggests that very few of these banks will eventually fail, so including them in hazard rate calculations creates a downward bias by inflating the survival function $1 - F(t)$. Duration models can adjust for this problem by estimating the probability that censored banks will eventually fail, and then weighting the censored observations by this probability before estimating the parameters of the hazard function. (See the appendix for more details.)

The sample banks differ in terms of their geographic location, their organizational form, and their primary regulator. These characteristics could make a bank more or less likely to fail, or given that a bank does fail, these characteristics could influence how quickly it fails. For example, banks located in depressed economic regions will be more likely to fail and, absent regulatory intervention, will fail more quickly than banks located in economically healthy markets. Duration models can include a vector of independent variables, typically known as *covariates*, measuring the characteristics that vary across banks but remain constant for each bank over the sample period. I use a split population approach which estimates two regression coefficients for each of the covariates in the duration model. The first coefficient measures the covariate's impact on the probability that a bank will survive—a negative coefficient indicates that the covariate is associated with a lower probability of survival (higher probability of failure). The second coefficient measures the covariate's impact on a bank's duration—given that a bank will eventually fail, a negative coefficient indicates that the covariate is associated with a shorter duration (a faster failure).

The duration models I estimate include four covariates, each of which is expressed as a (0, 1) dummy variable. $OCC = 1$ if the bank holds a federal charter (as opposed to a state charter). The OCC has traditionally practiced a more lenient chartering policy than most state chartering authorities, relying on market

forces rather than administrative rules to determine the number of banks a market could support.[7] A negative coefficient on *OCC* would suggest that this policy caused new national banks to fail more often and/ or more quickly, on average, than new state-chartered banks. *INDEPENDENT* = 1 if the bank is either a free-standing business or a one-bank holding company (as opposed to being an affiliate of a multibank holding company) throughout the sample period. A negative coefficient on *INDEPENDENT* would suggest that banks not having access to the financial strength and managerial expertise of a multibank holding company tend to fail more often and/or more quickly. *MSA* = 1 if the bank is located in an urban area. Banks in urban areas face greater competition than rural banks, but also may have greater opportunities for diversification. A negative coefficient on *MSA* would suggest that, on balance, these conditions cause banks in urban areas to fail more often and/or more quickly than rural banks. *SW* = 1 if the bank is located in the southwestern states of Louisiana, Texas, or Oklahoma, which experienced large numbers of bank failures during the mid- to late 1980s due to disruptions in energy-related industries. One would expect the coefficients on *SW* to be negative, reflecting lower survival probabilities and shorter duration times for banks in this region.

I add these four covariates to the duration model merely to illustrate how conditions and events external to the bank can affect its probability of failure and its time to failure. These four variables are not meant to be an exhaustive list of such conditions. Similarly, the duration model I estimate here is by no means definitive of the duration model techniques available to researchers. Other duration approaches do exist, including those that allow for *time-varying covariates* (for example, changes in economic, regulatory, or competitive conditions during each bank's duration). However, the multiple approaches I employ (including the Z-score and actuarial hazard function analysis conducted above) serve the purpose of this study, which is to test the simple life-cycle theory of de novo bank failure summarized in figure 3.

Table 3 displays the results of the duration models estimated separately for newly chartered banks and established banks. The estimated probability that the average bank will eventually fail is 19.65 percent for de novo banks and 8.93 percent for established banks. Note that these estimated failure probabilities are somewhat higher than the raw failure percentages shown at the bottom of table 2. In each case, the estimated probability is higher than the raw percentage because of the possibility that some of the censored observations will eventually fail.

Although established banks are less likely to fail, those that do fail have relatively short durations. Of the established banks that are expected to eventually fail, half of them will fail within an estimated 9.8 quarters (about 2.5 years) after the beginning of the sample period. Consistent with the life-cycle theory, newly chartered banks fail more slowly than established banks. It takes an estimated 21.1 quarters (about 5.25 years) for half of the de novo banks that are expected to fail to do so.

These differences in average duration can be seen clearly in figure 5, which charts the estimated hazard rates from the de novo and established bank duration models. Each of these functions is plotted based on the estimated coefficients shown in table 3 and the average values of the covariates for each sample. In general, these two estimated hazard functions resemble the shapes displayed above in figures 3 and 4. Thus, after controlling for censored data and a variety of environmental conditions, the failure patterns of newly chartered banks still differ substantially from the failure patterns of established banks.

The estimated probability of failure for established banks starts out above zero; peaks at about 8 percent for banks that survive for two years; and then slowly declines as the bank failure wave dissipates (see figure 1). In contrast, the estimated probability of failure for de novo banks starts out at zero and remains lower than the established bank hazard rate for three years; increases rapidly and peaks at nearly 14 percent for banks the survive for seven years; and then declines relatively quickly and begins to approach the established bank hazard rate. Note that both of these hazard functions peak much higher on the vertical scale than did the actuarial hazard functions plotted in figure 4. Thus, by not controlling for censored observations and the overall low probability of eventual failure, the actuarial model substantially understated the hazard rates. Also, note that the hazard rates in figure 5 are in decline but are still positive at year 14, which reflects the non-zero probability of failure for the censored observations.

As expected, being located in one of the southwestern states reduces the probability of survival (or increases the probability of failure) for both de novo and established banks. Failing de novo banks also failed more quickly in this region, but failing established banks had longer than average durations. The latter result may indicate that regulators allowed troubled banks with longstanding business relationships (and, hence, more franchise value) more time to recover before stepping in to resolve them.[8] Being located in a metropolitan statistical area reduced the probability
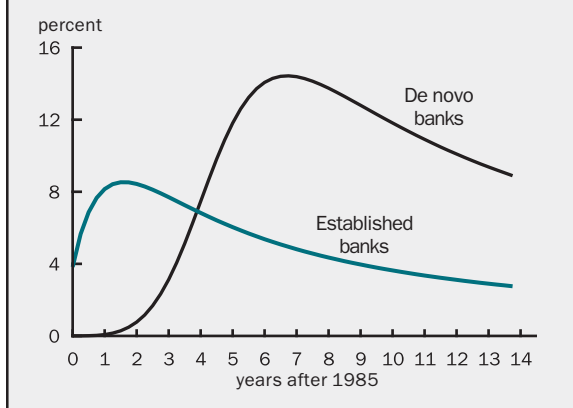
		De novo banks	Established banks
TABLE 3			
Selected results from parametric duration models			
Number of banks in sample		303	2,350
Average predicted failure probability		19.65%	8.93%
Predicted time for 50 percent of banks to fail		21.1 quarters	9.8 quarters
Probability of survival parameter estimates			
Constant		1.2930** (0.5144)	1.2475*** (0.2145)
OCC (= 1 if national bank)		0.0197 (0.2242)	–0.1296 (0.1117)
SW (= 1 if in Louisiana, Oklahoma, or Texas)		–0.3928* (0.2219)	–0.7419*** (0.0992)
MSA (= 1 if urban bank)		–0.5266* (0.3205)	0.2530** (0.1163)
INDEPENDENT (= 1 if independent or sole bank in a one-bank holding company)		–0.5265** (0.2386)	#
Survival time parameter estimates			
Constant		3.3045*** (0.6124)	2.3369*** (0.4489)
OCC		0.0075 (0.1376)	0.1354 (0.2339)
SW		–0.3243** (0.1386)	0.4753** (0.1971)
MSA		–0.2204 (0.5318)	0.5391** (0.2699)
INDEPENDENT		–0.1195 (0.1547)	#

*, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively.
Notes: Both models are estimated using the data sets described in table 2. Standard errors are in parentheses. # indicates that it was necessary to exclude the variable INDEPENDENT to make the established bank model converge. Further details on these models can be found in the appendix to this article.

FIGURE 5

Parametric hazard functions

of survival for de novo banks, but increased both the probability of survival for established banks and the survival time for established banks likely to eventually fail. Recall that intense competitive rivalry can cause banks to fail in urban markets, and that the lack of diversification opportunities can cause banks to fail in rural markets. The results suggest that these two phenomena affect de novo banks and established banks differently—on balance, de novo banks may be more sensitive to competition than to diversification risk, while small established banks may be more affected by a lack of diversification than by competitive rivalry. Being an independent bank or banking organization also reduces the probability of survival for de novo banks, which suggests that having access to the resources of multibank holding companies helps

new banks survive. (I excluded this covariate from the established bank model because its presence prevented the model from converging.) The identity of a bank's primary regulator (OCC or state) is not a significant determinant of the probability of survival or the survival time for either set of banks.

Conclusion

Like all new business ventures, banks start with a business plan but no guarantee of success. So, despite the regulatory safeguards of on-site examinations, capital requirements, and other risk controls, we should not be surprised to find that new banks are more likely to fail than established banks. This article offers a simple framework that explains not only *why* but also *when* new banks are likely to fail.

My results suggest that the primary determinant of new bank failure is *how new* the bank is. Ironically, de novo banks are relatively unlikely to fail during their first few years of operation when they are earning negative profits. They are relatively more likely to fail during the years of positive profits that follow. Brand new, but unprofitable, banks are typically protected from failure by large initial capital cushions. However, equity cushions at de novo banks typically decline to established bank levels *several years before* their earnings become stable enough to justify these relatively low levels of capital.

What are the implications of this result for capital regulation at newly chartered banks? If ensuring a high rate of survival for de novo banks is a regulatory objective, then this result offers support for requiring high levels of start-up capital for new banks, and for holding young banks to higher capital requirements. Higher levels of required capital will make newly chartered banks less vulnerable to failure. Under such policies, de novo entrants might be a more credible long-run deterrent to market power in consolidating local markets. Indeed, in the wake of the wave of de novo bank failures during the 1980s, federal bank supervisory agencies did impose higher capital requirements on newly chartered banks.

On the other hand, promoting the safety and soundness of the banking system does not require that regulators prevent all bank failures, much less all failures of new banks. At some point, attempting to improve the survival rate of de novo banks by increasing the amount of capital necessary for investors to secure the charter will act as an entry barrier. Similarly, increasing the required capital ratios for young banks with charters already in hand will, at some point, depress investors' expected rates of return and discourage investment in new banks. Higher capital requirements for young banks could also slow the rate at which they can grow their balance sheets, hampering the beneficial impact of new banks in markets where existing banks (perhaps with market power) are not adequately serving the banking public.

What are the implications of this study for the bank chartering decision? During the period covered by this study, some state chartering authorities would approve or deny a charter application only after considering whether a local market "needed" an additional bank, based on the number of banks already serving the market and the expected rate of local economic growth. These restrictive chartering policies sought to reduce bank failure rates, and the financial disruptions that accompany them, by limiting competition in local banking markets. In contrast, the federal chartering authority practiced a liberal entry policy that explicitly ignored these "convenience and needs" issues, stressing instead the potential procompetitive benefits of de novo entry. My results indicate that the de novo national banks chartered in 1985 were no more likely to fail, or to fail quickly, than the de novo state banks chartered in that same year. This suggests that the benefits of a liberal chartering policy can be achieved without substantial increases in de novo bank failure rates. Additional research might confirm whether these findings, which are based on data from just 303 new banks chartered in a single year, also hold for banks chartered in other years and/or under different economic and regulatory circumstances.

APPENDIX

Split population duration models

The parametric hazard functions described in the text begin with the assumption that a population of N banks will fail over time period $(0,t)$ according to some probability distribution:

$$F(t) = \int_0^t f(t)dt,$$

where t represents time and $f(t)$ is the probability density function associated with $F(t)$. The hazard function $h(t)$ can then be written as a function of $F(t)$ and $f(t)$ as follows:

$$h(T) = \frac{f(T)}{1 - F(T)} = \frac{f(T)}{S(T)},$$

where $S(t) = 1 - F(t)$ is the survival function and $0 < T < t$. Thus, $h(T)$ gives the probability (that is, the hazard rate) that a bank will fail at T conditional on surviving until T.

The general shape of the estimated hazard function will depend on the underlying probability distribution chosen to fit the data. I use the log-logistic distribution because it is capable of producing the hazard function shapes hypothesized in figure 3. The log-logistic distribution imposes the following functional forms on the hazard and survival functions:

$$h(t) = \frac{\lambda p (\lambda p)^{p-1}}{1 + (\lambda t)^p}$$

$$S(t) = \frac{1}{1 + (\lambda t)^p},$$

where the parameters p and λ give the hazard function its exact shape. The parameter p captures *duration dependence* or whether the hazard rate increases or decreases across time. The parameter λ captures the portion of the hazard rate that is time-invariant. This parameter, which can take on different values for different banks, is expressed as follows:

$$\lambda_i = e^{-\beta' X_i},$$

where the bank index i ranges from 1 to N, and X_i is a vector of bank-specific covariates that do not vary over time. Table 3 reports the estimated values of β under the heading "survival time parameter estimates." I use these β estimates to evaluate the above expression at the means of the covariates, which results in

$\lambda = 0.0474$ for the average de novo bank and 0.1019 for the average established bank. The parameter p is a constant that does not vary across banks; it equals 5.0175 for the de novo bank model and 1.6333 for the established bank model.

All of the parameters of the duration models in this study were estimated using maximum likelihood techniques. The standard estimation procedure for duration models starts with the following likelihood function:

$$L = \prod_{i=1}^N \left[f(t_i | p, \beta) \right]^{Q_i} \left[S(t_i | p, \beta) \right]^{1 - Q_i},$$

where $Q_i = 1$ if bank i failed during the sample period (an uncensored observation) and $Q_i = 0$ if bank i survived or was acquired during the sample period (a censored observation). Substituting $h(t)/S(t)$ for $f(t)$ and performing a log transformation produces the log-likelihood function to be maximized:

$$\ln L = \sum_{i=1}^{UC} \ln h(t_i | p, \beta) + \sum_{i=1}^N \ln S(t_i | p, \beta),$$

where $i \leq UC$ are the uncensored observations. Once I have estimated the parameters p and β, I can calculate the median time to failure by setting $S(t) = 0.50$ and solving for t.

This standard approach is based on the assumption that all of the censored banks will eventually fail (or would have eventually failed had they not been acquired). This assumption is inappropriate for the data used here, however, because over 80 percent of the de novo banks were censored observations, and over 90 percent of the established banks were censored observations. Given the nature of the data, I use a more general framework that avoids making this assumption. In the *split population duration model*, an additional estimable parameter δ, the probability that a bank eventually fails, enters the likelihood function as follows:

$$L = \prod_{i=1}^N \left[\delta f(t_i | p, \beta) \right]^{Q_i} \left[(1 - \delta) + \delta S(t_i | p, \beta) \right]^{1 - Q_i}.$$

Both Cole and Gunther (1995) and Hunter, Verbrugge, and Whidbee (1996) estimate split population models of financial institution failure. Note that this formulation collapses to the standard framework when $\delta = 1$. But when $\delta < 1$, the functions $S(t)$ and $f(t)$ become *conditional on* the bank eventually failing. Thus, the estimated hazard function $h(t) = f(t)/S(t)$

will not be unduly influenced by censored observations of banks that have little chance of ever failing. The parameter δ can vary across banks as a function of a bank's covariate values:

$$\delta_i \;=\; \frac{1}{1 + e^{\alpha' X_i}}.$$

Table 3 reports the estimated values of α under the heading is "probability of survival parameter estimates." I use these α estimates to evaluate the above expression at the means of the covariates, which results in $\delta = 0.1965$ for the average de novo bank and 0.0893 for the average established bank.

The hazard functions plotted in figure 5 show the probability that the average bank will fail at time t, given that the bank has not yet failed *but will eventually fail*. Thus, the shapes of the plotted hazard functions are based on the estimated values of λ and p, but not on the estimated values of δ.

NOTES

[1]Note that such ambiguity is largely absent from studies that examine the determinants of local market entry by already established banks. For a recent example, see Amel and Liang (1997). In general, these studies tend to find that established banks are more likely to enter highly profitable local banking markets, but less likely to enter highly concentrated local banking markets. Of course, the causes and consequences of a new bank start-up may be quite different from the causes and consequences of market entry by an already established bank.

[2]Seelig and Critchfield (1999) find that, on average, the state chartering authorities remain relatively more likely than the OCC to consider the ability of local banking markets to support an additional bank when evaluating a charter application. The authors show that income per capita per branch in the local banking market was a substantially stronger predictor of de novo state bank entry than of de novo national bank entry between 1995 and 1997.

[3]See DeYoung and Hasan (1998) for a more complete review of this literature.

[4]Examples of studies that have used hazard rates to analyze financial institution failure include Whalen (1991); Wheelock and Wilson (1995); Cole and Gunther (1995); Helwege (1996); and Hunter, Verbrugge, and Whidbee (1996).

[5]The Z-score is a measure of the probability that a firm's losses (negative profits) will exceed its equity capital. See Brewer (1989) for a discussion of the Z-score and its use in banking research.

[6]There are a number of possible reasons for this. In general, Z-score analysis performs best when used to represent the likelihood that an individual firm will become insolvent and, as such, Z-scores are typically constructed based on the known distribution (the mean and standard deviation) of ROA for an individual firm. In contrast, these average Z-scores are constructed for groups of banks, and rely on the cross-sectional distribution (the median and standard deviation) of ROA for each group of banks. As mentioned in the text, the distribution of ROA is not normally distributed, but rather is relatively skewed. Hence, it would be inappropriate to use the absolute levels of these average Z-scores to draw statistical inferences about the probability of bank failure.

[7]See Hunter and Srinivasan (1990) and DeYoung and Hasan (1998) for discussions that compare historical federal and state chartering policies.

[8]There are many potential reasons for the high bank failure rates in Texas, and for the relatively shorter durations for de novo banks in Texas, during the 1980s and 1990s. These reasons include unexpected economic shocks, unit banking restrictions that limited geographic diversification, a relatively undiversified regional economy, and regulatory failure.

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