The Performance of Internet-Based Business Models: Evidence from the Banking Industry* — Source link

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The Performance of Internet-Based Business Models: Evidence from the Banking Industry*

The initial Internet bank startups tended to underperform branching bank startups. This suggested that Internet-only business models were not economically viable for banks. However, firms that pioneer new business models may benefit substantially from experience as they grow older, and firms that use automated production technologies may benefit from scale effects as they grow larger. Econometric analysis of Internet-only bank startups finds strong evidence of the latter, but not the former, effect. The results suggest that Internet-only banking success depends on attaining sufficient scale and strong management practices.

I. Introduction

As the Internet becomes more important for commerce, Internet Web sites are playing a more central role in most companies' business plans. An especially elegant case has been made for the "Internet-only" business model in the banking industry. Overhead expenses can be reduced by jettisoning physical branch offices. Banks can use the resulting savings to reduce their loan interest rates or increase their deposit interest rates, attracting new customers without sacrificing earnings. The web-based distribution focus allows banks to enter new geographic markets without the costs of acquiring existing banks or starting up new branches, further increasing growth potential.

Nearly half of all U.S. banks and thrifts were operating transactional Internet Web sites at the beginning of 2002.[1] But most of these firms have

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1. A transactional Web site allows customers access to banking services without leaving their homes or offices. The most basic transactional Web sites allow customers to check account balances and transfer funds between accounts. More-advanced

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adopted a "click-and-mortar" business model in which an Internet Web site is used to complement existing brick and mortar branches. Only a few dozen banks and thrifts have adopted a pure Internet-only strategy that eschews physical branches entirely; by-and-large, these firms have generated sub-par earnings. For every Internet-only bank or thrift that has achieved marginal levels of profitability, another has exited the market through liquidation or acquisition or has abandoned the pure Internet-only business model and established physical branches. Government regulators have become increasingly risk averse with banks and thrifts that deploy, or wish to deploy, this business model.

This article analyzes the financial performance of a dozen Internet-only banks and thrifts that started up between 1997 and 2001. Newly chartered (de novo) Internet-only banks and thrifts provide a clean test of the Internet-only business model, because unlike a bank that converts from a branching model to an Internet-only model, their financial performance is unaffected by any production structures or client relationships left over from a preexisting business model. To separate the performance effects of the Internet-only model from the performance effects of "newness," a sample of 644 branching banks and thrifts that also started up between 1997 and 2001 are used as a performance benchmark. The analysis attempts to identify which components of the Internet-only business model have worked well and which have worked poorly, determine why some banks and thrifts have been able to deploy this model more successfully than others, and ascertain whether the Internet-only business model could be economically viable for banks and thrifts in the long run, despite its poor short-run performance. (For the remainder of this article the generic term *banks* often is used in place of *banks and thrifts,* and the terms *startup bank* and *de novo bank* are used interchangeably.) Although the focus here is on Internet-only banks and the potential viability of the Internet-only business model, some tentative inferences about the economics of the click-and-mortar business model can be drawn from the empirical results.

This article also introduces a general intuitive framework for analyzing the performance of startup firms that use new or nontraditional technologies. For a typical startup firm that uses existing technology, the process by which accumulated experience is transformed into improved financial performance is characterized as general experience effects, and the process by which increased firm size is transformed into improved financial performance is characterized as general scale effects. However, a startup firm that uses a new or nontraditional technology may internalize additional experience effects or additional scale effects. These

Web sites allow customers to open new accounts, apply for loans, manage investments, receive bills, and pay bills. The point estimate of "nearly half of all U.S. banks and thrifts" is based on the 49.7% Internet Web site adoption rate at national banks as of 2001:Q4 (source: Office of the Comptroller of the Currency staff).

processes are characterized as technology-based experience effects and technology-based scale effects. The empirical analysis tests for the existence and estimates the magnitude of these four effects for startup banks and thrifts. If either technology-based experience effects or technology-based scale effects exist and are substantial for newly chartered Internet-only banks, then the performance of these banks may improve over time and the Internet-only business model could prove to be economically viable.

The empirical analysis applies an assortment of estimation techniques and regression specifications to quarterly time-series cross-section financial data. Given the small number of Internet-only banks and thrifts available for testing, care is taken to ensure that the results are not driven by a small number of outlying observations or by the idiosyncrasies of an individual bank or thrift. By and large, these alternative tests generate robust results. On average, Internet-only startup banks are substantially less profitable than branching bank startups. The typical Internet-only bank successfully executes some elements of the business model (e.g., rapid growth, better prices on loans and deposits) but not others (e.g., lower overhead expenses). Although there is little evidence that Internet-only startups enjoy steeper learning curves than traditional startup banks, the data suggest that Internet-only banks have access to deeper scale economies than branching banks—and as a result, the initial performance gaps between the two sets of banks narrow as the banks grow larger. These effects are strongest for a subset of arguably better-run Internet-only "survivor" banks that are (as of the drafting of this article) still actively pursuing an Internet-only business strategy. However, because Internet bank startups hold relatively more equity capital than traditional bank start-ups—to fund rapid expected asset growth and satisfy relatively more-stringent regulatory standards—these performance gains have not yet translated into improved rates of return for investors in these ventures.

The remainder of the article proceeds as follows. Section II provides a brief introduction to the Internet-only business model, documents the financial performance of banks and thrifts that have implemented this strategy, and reports on the regulatory environment facing these firms. Section III reviews some of the previous literature on topics that play a central role in this study: learning and experience effects, bank scale economies, and Internet bank performance. Section IV presents an intuitive framework for identifying differential experience effects and scale effects at traditional startup firms and innovative startup firms. Section V describes the data. Section VI provides a preliminary analysis of the data and generates some evidence consistent with the existence of technology-based experience and scale effects at Internet-only banks. Section VII presents the statistical models used in the main empirical tests, and section VIII presents the results of those tests. Section IX summarizes the article and draws some forward-looking conclusions for the role of the Internet in the banking industry.

II. The Internet Banking Environment

The Internet distribution channel can add value to banking franchises in a number of ways, depending on whether it is used to augment physical branches (click-and-mortar banks) or in place of physical branches (Internet-only banks). The strategic core of the click-and-mortar banking model is to route standardized, low-value-added transactions (e.g., bill payment, balance inquiries, account transfers, credit card lending) through the inexpensive Internet channel, while routing specialized, high-value-added transactions (e.g., small business lending, personal trust services, investment banking) through the more expensive branch channel. By providing an option for customers who want to do some but not all of their banking over the Internet, a click-and-mortar bank may be better able to retain its most-profitable customers. In contrast, the strategic core of the Internet-only business model is to reduce overhead expenses by completely eliminating the physical branch channel. If this results in lower fixed costs, Internet-only banks can set narrower variable margins (by paying higher deposit rates or charging lower fees and lower loan rates) but still maintain normal returns on assets and equity. Narrower margins should grow the bank faster by bidding customers away from competitors, resulting in faster earnings growth.

But the Internet is not merely a distribution channel for banks: adopting an Internet Web site can affect a bank's production function and alter its product mix, and these effects are likely to be strongest at Internet-only banks. Internet-only banks are poorly suited for "relationship lending," in which risk is assessed via personal knowledge and direct monitoring of idiosyncratic borrowers (e.g., small business loans or farm loans) and are better suited for "transactions lending" in which borrowers apply for loans on-line, risk is assessed via automated credit scoring models and controlled via large numbers diversification and securitization of relatively homogeneous credits (e.g., mortgage loans, auto loans, and credit card loans). Thus, the choice of a distribution strategy—and by extension, the choice of a loan production process—is likely to have implications for optimal bank size. Because automated lending technology exhibits a low ratio of variable costs to fixed costs, Internet-only banks may have access to greater scale economies than traditional branching banks.

Most Internet-only banking franchises in the United States have struggled for profitability.[2] Some have exited the market, via either

2. A sampling of the problems encountered by Internet banks includes difficulty retaining core deposits, low revenues from cross-selling, high expenses to provide depositors access to foreign ATMs, and higher than expected overhead expenses for marketing, technological infrastructure, and 24-hour call centers. See DeYoung (2001) for a detailed discussion of the shortfalls of the Internet-only banking model.

acquisition, voluntary liquidation, or regulatory closure.[3] Others have remained in the market but changed strategies, augmenting their transactional Web sites with physical branches.[4] Similarly, a number of the large banking companies that launched "trade name" Internet-only ventures have integrated these business units back into the main bank.[5] However, a small number of Internet-only banking franchises have achieved some measure of profitability and (at the time this article was prepared) remain committed to this business model in the long run. Ironically, anecdotal evidence suggests that "old-fashioned" management practices like cost control, conservative growth, and strategic focus are important keys to success for these "new-fashioned," high-technology banks.[6]

Government regulators have increasingly paid close attention to Internet-only banks, because these banks tend to be young, grow rapidly, and have lower than average earnings. To support rapid asset growth and absorb early losses, regulatory authorities require higher levels of startup capital before approving a new Internet-only bank charter, and bank supervisors require higher capital-to-asset ratios while these banks are young.[7] Some Internet-only bankers have claimed that processing times for charter applications and deposit insurance applications are substantially slower and supervisors tend to micromanage their activities more so than at traditional banks.[8] Whether these supervisory and regulatory restrictions are necessary for Internet-only banks to be safe and sound or supervisors and regulators are being risk averse because the performance characteristics of this new business model are not yet fully known is not clear on balance. Excessively tight supervision and regulation imposes direct costs on the first generation of Internet-only banks and, by potentially stifling innovation or slowing the rate of innovation,

3. For example, Lighthouse Bank (an Internet-only commercial bank) was acquired by Brookline Savings Bank in July 2001, G&L Bank (an Internet-only thrift) filed an application with its regulator to voluntarily liquidate in October 2001, and NextBank (an Internet-only credit card bank) was closed by the FDIC in February 2002.

4. For example, ClarityBank.com switched from an Internet-only strategy to a click-and-mortar strategy in the latter half of 2001 and changed its name to National American Bank in 2002.

5. A trade-name bank is a separately managed but not separately chartered or capitalized Internet-only subsidiary of a traditional branching bank. The most notable example of a trade-name bank was WingspanBank.com, launched as an operating unit of Bank One Corporation in mid-1999 but absorbed back into the main bank in June 2001.

6. See "Net Survivors: Conservative Strategy Is Key," *American Banker* (November 13, 2001): 1.

7. See "Would-Be Web Banks Call FDIC Too Slow," *American Banker* (February 21, 2001): 1; and "OTS Finding Web Banks a Regulatory Handful," *American Banker* (September 21, 2000):1.

8. See "After NextBank, Doubts on Internet-Only Model," *American Banker* (February 11, 2002): 1; and "Would-Be Web Banks Call FDIC Too Slow," *American Banker* (February 21, 2001): 1.

could impose indirect costs on the second generation of Internet-only banks by reducing their opportunities for spillover learning.

III. Relevant Literature

The theoretical framework introduced in this article, as well as the empirical testing of that framework, rests on the findings of previous research in three areas: experience effects, bank scale economies, and Internet bank performance. The literature in each of these areas is briefly reviewed here.

A. Learning and Experience Effects

Research on learning by doing began with a peculiarity observed in the airframe manufacturing industry at the close of the Second World War. British-manufactured airframes and U.S.-manufactured airframes were of comparable quality, but U.S. companies could produce airframes more quickly or at less expense than the British companies. Asher (1956), Arrow (1962), Alchian (1963), Hartley and Corcoran (1978), and others developed the idea of experience effects to explain this difference in performance. The concept is often expressed as follows: holding production technology and firm size constant, unit costs fall as a firm accumulates experience using the technology. Based on information from 97 firms in a variety of industries, Ghemawat (1985) found that a doubling of experience was typically associated with between a 10%–25% decline in unit costs, where "experience" is defined as a 100% increase in accumulated production between two points in time.

However, as pointed out by Griliches (1979), using accumulated production to measure a firm's stock of experience or knowledge can be problematic, in part because firms gain knowledge not just from their own investment and production activities but also via spillover effects from competitors, suppliers, customers, universities, or government. This point argues for an experience measure that is broader than accumulated production; this study uses accumulated time as a proxy for a bank's stock of experience.

Experience effects have not been extensively measured in banking.[9] However, a handful of studies—Rose and Savage (1984), Huyser (1986), Hunter and Srinivasan (1990), Brislin and Santomero (1991), DeYoung and Hasan (1998)—measured the rates at which the financial performance of de novo banks improves over time. For example, the last study estimated a "profitability time path" for de novo banks and found

9. One study, by Remolona and Wulfekuhler (1992), argued that finance companies that entered certain niche markets (e.g., leasing) earlier that their bank competitors benefited from "dynamic scale economies in information because of their early entry and accumulated experience" (p. 25). These authors did not explicitly measure a learning or experience curve.

that the typical 1990s de novo bank took about 9 years to become as profitable as an established bank, with over half of this improvement occurring during the initial 3 years of operation.[10]

B. Bank Scale Economies

The literature on commercial bank scale economies has been surveyed a number of times elsewhere (e.g., Gilbert 1984; Clark 1988; Humphrey 1990; Evanoff and Israilevich 1991; Berger, Hunter, and Timme 1993; Berger, Demsetz, and Strahan 1999). This literature evolved over time, and the current debate focuses on whether the very largest banks enjoy increasing returns to scale. Empirical research that uses standard techniques finds that scale economies are limited, with estimates of minimum efficient scale ranging between $10 billion and $25 billion. But a new strain of the literature argues that standard approaches do not properly account in the production function for the interplay between bank capital, bank risk levels, and managerial preferences (Hughes et al. 2001), and empirical models that attempt to account for these phenomena find that scale economies exist for even the largest banks. Although this new empirical approach has not been widely adopted, the results that it generates have some currency because they are consistent with the bank megamergers that continue to occur in the United States and Europe.

This banking scale economy "controversy" is a moot point for this study, because newly chartered banks fall well short of minimum efficient scale by any measure. A more germane question is whether the Internet-only business model gives banks access to deeper scale economies than the traditional branching model. There has not yet been a study of scale economies at Internet banks, but there is evidence of larger than average scale economies at banks that use technology-intensive production processes. Rossi (1998) found that mortgage banks (which rely heavily on automated lending technologies) have access to much larger scale economies than full-service commercial banks. Similarly, the recent consolidation of the credit card banking sector into a handful of very large competitors (again, banks that rely on automated lending technologies) also suggests the existence of deep scale economies for technology-intensive banks.

C. Internet Banking

The diffusion rate of Internet Web sites in the banking industry has been rapid. The first Internet banking Web sites were not launched until 1995,

10. Regulatory economists have focused on the age of new banks, rather than their accumulated output, because like most business startups, newly chartered banks can be financially fragile. Government supervisors responsible for detecting early signs of financial problems can gain insight from studying the progress of young banks as they evolve over time into mature banks.

but nearly half of U.S. banks and thrifts were allowing customers to perform banking transactions over the Internet by 2002.[11] Two studies have attempted to identify the conditions that cause banks to adopt this technology. Furst, Lang, and Nolle (2002) found that a national bank in 1998 was more likely to offer Internet banking if it was large, well-run (high return-on-equity, low noninterest expenses, good supervisory exam ratings), located in an urban area, an affiliate in a bank holding company, incurred high amounts of branch network expenses, and generated large amounts of noninterest income. Courchane, Nickerson, and Sullivan (2002) derived two testable implications from a theoretic model: firms are more likely to be early adopters of new technology when they are strategically large relative to their rivals and when uncertainty about demand for the services produced with the new technology is low. They explored the data for banks in the Tenth Federal Reserve District in 2000 and found significant empirical support for these theoretical implications.

Three previous studies examined the financial performance of Internet banks. The first two studies employed a broad definition of Internet bank that includes both click-and-mortar banks and Internet-only banks. Sullivan (2000) found that Internet banks in the Tenth Federal Reserve District incurred somewhat higher expenses but generated somewhat higher fee income and concluded that "in general banks have been neither helped nor harmed by their early commitment to the Internet as a delivery channel" (p. 12). In contrast, Furst et al. (2002) studied the profitability (return on equity) of national banks in 1999 and found that Internet banks tended to outperform non-Internet banks on average. However, both studies found that de novo Internet banks earned lower profits than non-Internet de novo banks. The third study examined the financial performance of six Internet-only banks and thrifts. Consistent with the de novo bank results of the other two studies, DeYoung (2001) found that the average Internet-only bank (which was only about 1 year old) earned significantly lower profits than the average 1-year-old branching bank, due primarily to low business volumes and high noninterest expenses.

IV. Experience Effects and Scale Effects

This article proposes and tests for the existence of four separate but simultaneous performance processes at newly chartered Internet-only banks. This framework generalizes to any industry in which new firms

11. In 1995, Wells-Fargo became the first bank to give its customers online access to account statements, and Security First Network Bank became the first Internet-only bank. (In 1998, the Royal Bank of Canada acquired and recapitalized Security First, but the Internet-only strategy was retained. In August 2001, Security First was dismantled and its transactions accounts were sold to Centura Bank, a brick-and-mortar subsidiary of Royal Bank.)

enter the market using a production technology or business plan that is distinctly different from that employed by incumbent firms. Banking provides an especially appropriate test for this framework, because new bank startups occur with regularity and a number of recent bank startups have employed an innovative Internet-only business plan and production technology.

The first two processes are common to all newly chartered banks, regardless of their business models (Internet-only, click and mortar, or brick and mortar). As discussed earlier, previous research established that newly chartered banks substantially underperform established banks at first, but these performance gaps systematically diminish over time as new banks grow older and larger. General experience effects occur as a new bank ages and, by doing so, accumulates general banking experience and knowledge of the local market. As this general experience accumulates, it is transformed into improved financial performance through learning-based improvements in pricing, marketing, cost control, risk management, employee relations, competitive strategy, and the like. General scale effects occur as a new bank grows larger. Increased size is transformed into improved financial performance primarily through lower per-unit costs, although increased size can also produce revenue efficiencies, as a new bank gains access to new product markets (e.g., middle-market lending or loan participation). Because age and size are positively correlated at young banks, experience effects and scale effects are unavoidably intertwined. In this study, "experience" is measured indirectly by a bank's age, holding bank size constant in multiple regression tests.

The second two processes occur only at startup banks with business models based on new or nontraditional technologies: in this study, newly chartered Internet-only banks. Technology-based experience effects occur as a new Internet-only bank ages and its managers, employees, and perhaps even its customers accumulate experience with the new technology. As with the general experience effect, the accumulation of technology-based experience can get transformed into improved financial performance through any number of bank behaviors. If technology-based experience effects exist, they are additive to general experience effects; that is, a new Internet-only bank consumes them over and above the experience effects to which all new banks have access. Similarly, Internet-only banks may experience technology-based scale effects that are additive to general scale effects. Web-based applications are often said to be "scalable," which narrowly defined refers to constant returns to scale, that is, adding an additional server to a network of computers does not induce diminishing returns (increased per-unit costs). However, given their similarities to financial institutions like mortgage banks and credit card banks that achieve high volumes and low unit costs by using automated production, marketing, and distribution techniques

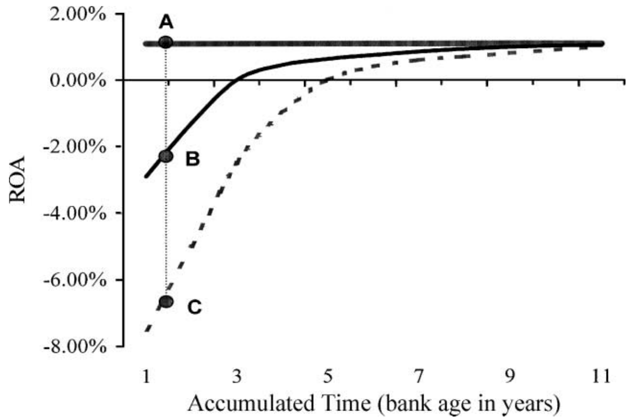

FIG. 1.—Hypothetical time paths for return-on-assets (ROA) at newly chartered banks.The thick solid line represents a performance benchmark, the average ROA for small established banks. The thin solid line is a time path for ROA at newly chartered branching banks, shaped like those found in previous empirical studies (e.g., DeYoung 1999). The dashed line is a hypothetical time path for ROA at newly chartered Internet-only banks.

(online price discovery and loan applications, credit scoring models to evaluate risk, loan securitization to manage risk, automated billing for loan servicing), it seems plausible that Internet-only banks could exhibit deeper scale economies than traditional branching banks.

If only the general experience and general scale effects exist in meaningful magnitudes, then the financial performance of Internet-only startups and traditional branching startups improve at similar rates as these banks grow and mature. However, if technology-based experience or technology-based scale effects exist in meaningful magnitudes, then the financial performance of new Internet-only banks improve more quickly than new traditional banks. The latter scenario is illustrated in figure 1, where accumulated time (bank age) on the horizontal axis indirectly measures accumulated experience, and return on assets (ROA) on the vertical axis measures bank financial performance. Previous research finds that traditional de novo banks (thin solid line) initially underperform established banks (horizontal solid line) but gradually catch up over time. Holding bank size constant, the rate at which the ROA-gap *AB* diminishes is driven by general experience effects. (If a similar figure were drawn with assets on the horizontal axis, the closing of the ROA-gap *AB* could be attributed to general scale effects.) Previous research also finds that Internet-only de novo banks initially underperform traditional de novo banks, but little is known about whether and how the ROA-gap *BC* behaves over time. The dashed line running through point *C* is just one of many possible ROA time paths for Internet-only banks. It characterizes the financial performance of Internet-only startups improving over time and eventually catching up with traditional bank startups, with the diminishing ROA-gap *BC* driven by technology-based experience effects.[12] (If a similar figure were drawn with assets on the horizontal axis, the closing of the ROA-gap *BC* could be attributed to technology-based scale effects.)

The regression analysis that follows tests for the existence of general and technology-based experience and scale effects, estimates their magnitudes, and identifies the aspects of financial performance through which these effects are most-strongly manifested. Each of the important parameters in figure 1 is estimated, including the static performance difference between Internet-only startups and branching startups (i.e., the performance gap *BC*), the slope of the performance time path for branching banks (i.e., general experience effects), the slope of the performance path with respect to the size of branching banks (i.e., general scale effects), changes in the performance gap *BC* as banks grow older (i.e., the relative slopes of the two performance time paths or technology-based experience effects), and changes in the performance gap *BC* as banks grow larger (i.e., technology-based scale effects).

The conventional measure of experience used in the learning-by-doing literature is accumulated production. However, this is a problematic measure at banks that are, by definition, multiple-output firms.[13] This study uses accumulated time (i.e., bank age) as a proxy for experience. This is a good proxy if the firms being compared are approximately equal in size, so that elapsed time provides a good approximation of output-based experience. In the United States, newly chartered banks

12. If the two ROA time paths in figure 1 are viewed as streams of expected future returns from an initial investment at $t = 0$, then the net present value of an Internet-only bank startup would be less than the net present value of a traditional bank startup (assuming equal risk). In such a world, rational investors would not start up Internet-only banks; however, an Internet-only bank that had already started once the information in figure 1 became known might continue to operate, depending on the liquidation values of the assets already in place relative to the cash flows going forward. There are plausible ROA time paths different from those shown in figure 1 that have different implications for future investments in new Internet-only banks. (For example, the net present values of the two investments at $t = 0$ might be identical if the Internet-only ROA path reached the traditional de novo bank ROA level by, say, year 2 and reached the mature bank benchmark ROA by, say, year 4.) In addition, if a second generation of Internet bankers benefits from learning spillovers based on the experiences of the first generation of Internet bankers, the time path for the second generation could arguably start out with a higher ROA at $t = 0$ or have a steeper slope.

13. Asset-based production measures omit transactions-based services produced for depositors, omit fee-based services that do not appear on the balance sheet (e.g., credit enhancements, trust services, mutual fund sales), and entangle experience effects with scale effects. Deposit-based production measures omit credit-based services produced for borrowers, omit fee-based services, and entangle experience effects with financing decisions. Flow-based production measures (like the number of payments transactions or the number of loan accounts) are preferable, but banking databases do not systematically record these numbers and, in any event, aggregating flow measures across different product lines is problematic.

tend to be similar in size due to safety and soundness regulations.[14] Minimum absolute levels of startup capital are necessary to qualify for a bank charter, which sets a lower limit on startup size, and stringent capital-to-assets requirements for young banks place a brake on asset growth. Nevertheless, an asset-size control variable is included in all the regressions in which age-based experience effects are estimated.

V. The Data

The key to evaluating the Internet-only banking model is to compare the performance of the banks that use it (which, by definition, are new bank startups) to the performance of new bank startups that use the more traditional branch-based banking model. The Internet-only sample consists of 12 banks and thrifts newly chartered in the United States between 1997 and 2000 whose primary point of customer contact is a transactional Web site. The benchmark performance sample consists of 644 banks and thrifts newly chartered in the United States between 1997 and 2000 whose primary point of customer contact is a physical branch. Both samples are quarterly data panels that include multiple observations of each bank as it ages.

To be included in the Internet-only sample, banks and thrifts had to meet six conditions. These conditions ensure that the firms in the Internet-only sample are "typical new bank startups" in every way except that they produce, market, and distribute their financial services over the Web rather than through physical branches; in other words, imposing these conditions ensures that the tests that compare the financial performance of these two sets of banks produce valid statistical inferences. First, the firm had to be a separately chartered bank or thrift (i.e., not a "trade name") regarded by its primary regulator to be operating primarily through the Internet. Twenty-three such institutions were operating in the United States at the end of the sample period (2001:Q2). Second, the firm had to start its life by obtaining a new bank or thrift charter from a state or federal regulator or by purchasing an existing bank or thrift charter and relaunching the firm as an entirely new institution.[15]

14. U.S. commercial banks at least 10 years old ranged from $10 million to $500 billion in assets in 2000. The quartiles (i.e., the 25th , 50th, and 75th percentiles) of the commercial bank asset size distribution were $40 million, $80 million, and $190 million, respectively. By comparison, the asset-size distribution of newly chartered banks was relatively homogeneous. For example, urban banks and thrifts chartered in the initial year of this study (1997) ranged in size from $2 million to $225 million in assets 90-180 days after they opened, and the asset size quartiles were $12 million, $17 million, and $24 million.

15. Charter conversions were allowed into the data set only when all the following events occurred at relaunch: all preexisting branch operations were shut down; all the bank's assets, loans, and deposits fell dramatically; the bank received a substantial injection of equity capital from its new owners; and the bank's earnings were negative in its first full quarter of operations (as is typical of a new bank startup).

Third, the new firm had to offer a full range of basic banking services over the Internet, including taking insured deposits, offering checking accounts, and making loans.[16] Fourth, banking had to be the principal activity of the new firm, not just an ancillary activity.[17] Fifth, the new firm had to have less than $300 million in assets at the end of its first full quarter of operation.[18] Finally, the firm had to be operating for at least two full quarters as of the end of the sample period. The 12 Internet-only banks and thrifts that met these conditions are listed in table 1.[19]

The benchmark sample includes newly chartered banks and thrifts that also met the conditions listed earlier, with the exception that they were regarded by their primary regulators as operating primarily through physical branches. In addition, the benchmark sample is limited to banks that started up between the beginning of 1997 and the end of 2000 (the time period over which the 12 Internet-only banks entered the market) and were located in urban markets (this excludes rural banks that rely heavily on agricultural loans, a line of business not engaged in by Internet-only banks). Although the benchmark sample contains primarily

16. This condition excludes so-called Internet banks that actually rely quite heavily on physical branch locations. For example, this condition rules out hybrid banks that gather deposits through their Web sites but make loans at physical branches (e.g., Landmark Bank, a.k.a. Giantbank.com), as well as those that make loans through their Web site but gather deposits at physical branches (e.g., Indy Mac Bank). This condition also excludes banks that gather deposits at far-flung networks of Internet kiosks located at grocery stores or other retail establishments, and invest those funds in securities or upstream them to their parent holding companies rather than using them to make loans (e.g., CIBC National Bank, a.k.a., MarketPlace Bank). Finally, this condition excludes credit card Internet banks (e.g., NextBank, the banking subsidiary of NextCard, which failed in February 2002) that use very little deposit funding.

17. For example, the online banking services provided by the Internet-only bank BMW Bank of North America are ancillary to the sales of automobiles at BMW dealerships, and the online banking services provided by E*Trade Bank are marketed primarily to the online brokerage clients of its parent company E*Trade. Imposing this condition ensures that the banks in the Internet-only sample focus on traditional banking markets and identify traditional banks (such as those in the benchmark sample) as their main competitive rivals, rather than commercial firms or nonbank financial firms.

18. Banks that are exceptionally large when they start up are likely to be "learning" (based on their larger size and larger production throughput) at a pace well in excess of the typical startup bank, so including such banks in the Internet-only sample would make it difficult to test for technology-based experience effects. This condition also excludes banks that were set up using assets and asset relationships transferred from existing firms and, as such, are not truly startup ventures. For example, BMW Bank started up with $500 million in automobile loans, and E*Trade Bank started out with $3 billion of preexisting loans from its nonbranching predecessor Telebank. Although $300 million in assets is an arbitrary cutoff, all the banks excluded by this condition from the Internet-only sample also failed to meet at least one of the other five conditions.

19. The 11 (out of 23) firms that did not qualify for the Internet-only sample were excluded for one or more of the following reasons: 2 firms started with converted charters but retained assets and relationships developed during the previous banking regime, 8 firms either did not offer a full range of banking services over the Internet or relied heavily on physical channels (e.g., kiosks, loan development offices, or "narrow branches" that accepted deposits but did not market loans) to supplement their Internet channel, 3 firms started up with assets in excess of $300 million, banking was an ancillary rather than the primary activity at 2 firms, and 1 firm had not yet been operating for two full quarters.

TABLE 1 Internet-Only Banks and Thrifts Included in the Sample

	Charter	First Full Quarter of Data Used in Tests	Assets ($ Millions) at the End of Bank's First Full Quarter	Number of Quarterly Observations Used in Tests	Assets ($ Millions) at the End of the Sample Period	Exit Strategies at or after the End of the Sample Period
Bank of Internet, USA, San Diego, CA*	New thrift charter	2000:Q4	$62	3	$154	
ClarityBank.Com, Uvalde, TX	Converted national bank charter	2000:Q2	$43	5	$118	Abandoned Internet-only strategy in 2000:Q3
DeepGreen Bank, Seven Hills, OH*	New thrift charter	2000:Q4	$213	3	$280	
First Internet Bank of Indiana, Indianapolis, IN*	New state bank charter	1999:Q1	$15	10	$232	
G & L Bank, Pensacola, FL	New thrift charter	1999:Q4	$29	7	$99	Voluntary liquidation in October 2001
Lighthouse Bank, Waltham, MA	New state bank charter	2000:Q3	$41	4	$79	Acquired by a branching bank in July 2001
NetBank, Alpharetta, GA*	New thrift charter	1997:Q4	$90	10	$1,435	

Nexity Bank, Birmingham, AL*	Converted state bank charter	2000:Q1	$91	6	$311	
Principal Bank, Des Moines, IA*	New thrift charter	1998:Q2	$6	10	$238	
Security First Network Bank, Atlanta, GA*	Relaunched thrift charter	1999:Q1[†]	$114	10	$373	Abandoned Internet-only strategy in August 2001
The Bancorp.com Bank, Wilmington, DE*	New state bank charter	2000:Q4	$86	3	$104	
Virtual Bank, Palm Beach Gardens, FL*	New thrift charter	2000:Q3	$233	4	$251	

* Indicates banks included in the "survivor" data set.
[†] Security First was originally started as an Internet-only bank using a new thrift charter in 1995. It subsequently was purchased by Royal Bank of Canada in late 1998, recapitalized, and relaunched as a new Internet-only bank.

new brick-and-mortar banks, it unavoidably includes some click-and-mortar bank startups that operate both physical branches and transactional Web sites. Unfortunately, regulatory databases do not include the information necessary to systematically identify which branching banks have adopted Web sites, at what date they did so, and what percentage of their activity is run through their Web sites versus their branches. If technology-based experience effects and technology-based scale effects exist, they will likely occur with lower intensity at new click-and-mortar banks (which run only a portion of their activities through their Web sites) than at new Internet-only banks (which run 100% of their activities through their Web sites). To the degree that the benchmark sample contains some new click-and-mortar banks, it will be more difficult to reject null hypotheses regarding the existence of technology-based experience effects and technology-based scale effects at the new Internet-only banks.

The combined data set is an unbalanced panel of 4,742 quarterly observations of 656 banks and thrifts observed over a 17-quarter window from 1997:Q2 through 2001:Q2. Startup quarters are excluded from the data, because banks typically operate for less than 90 days during their startup quarters; thus, the sample period begins in the second quarter of 1997. Bank age (AGE) is set equal to 1 at the end of each bank's first full quarter of operations. The data panel is unbalanced for three reasons. First, the newly chartered institutions started up at different times. Second, a very small number of the institutions in the benchmark sample were acquired during the sample period.[20] Third, because high numerical values of AGE are observed only for banks chartered near the beginning of the sample period, while low numerical values of AGE are observed for all banks, banks are included in the sample only up to their tenth full quarter of operation.[21] This prevents the estimated slopes of the performance time paths (see fig. 1) from being unduly influenced by a few older, outlying banks.

The sample period ends with the second quarter of 2001, because 3 of the 12 banks in the Internet-only sample banks ceased to exist as Internet-only banks shortly after that quarter. A fourth abandoned the Internet-only strategy in late 2000. These four banks exited the business model in a variety of ways—one was acquired by a brick-and-mortar bank, one liquidated itself voluntarily, and two continued to operate after switching to click-and-mortar business models—but all four were solvent at the time they exited. Note that none of the banks in either sample failed during the sample period and, as mentioned earlier, only a handful of banks in the benchmark sample exited via merger during the sample period.

20. State laws restricting the acquisition of newly chartered banks account for the small number of exits by acquisition. As of the mid-1990s, 30 of the 50 states had some legal prohibition on the acquisition of de novo banks, ranging from between 3 years and 7 years after these banks were launched. See Amel (1993).

21. For example, just four of the Internet-only banks had reached AGE = 10 by the end of the sample period (2001:Q2).

Nevertheless, to address the potential for survivor bias among the Internet-only sample, all regression tests are performed for the full data set, which includes all 12 Internet-only banks, and again for a "survivor" data set, which excludes the four Internet-only banks in question. The full data set regressions estimate the performance of the average Internet-only bank or thrift, while the regressions using the survivor data set come closer to estimating the "best practices" performance possibilities of the Internet-only strategy.

VI. Initial Analysis of the Data

Table 2 presents means, standard deviations, and definitions for the variables used in the regression tests, based on panels of quarterly data from 1997:Q2 through 2001:Q2. The first 18 rows contain financial performance ratios used as endogenous variables in the regressions, and remaining rows contain exogenous regression variables as well as some additional descriptive variables. The statistics displayed in column 1 describe the population of small, established banks and thrifts (assets less than $1 billion and at least 10 years old) in urban U.S. markets during the sample period. Although the data in column 1 are not used in the regression tests, they are useful for comparative purposes: statistically significant differences between the means of the newly chartered benchmark banks in column 2 and the small established banks in column 1 provide evidence of the performance gap *AB* illustrated in figure 1. Similarly, significant differences between the means of the newly chartered Internet-only banks in column 3 and the newly chartered benchmark bank in column 2 provide evidence of the performance gap *BC*. Finally, significant differences between the means of the "surviving" Internet-only banks in column 4 and the benchmark banks in column 2 suggest that performance gaps like *BC* even for the better-run Internet-only banks. All the difference of means tests in table 2 control for the fact that banks are observed multiple times in each panel data set.[22]

A. Branching Startups (Col. 2) Relative to Small Established Banks (Col. 1)

Consistent with earlier studies, the financial performance of newly chartered branching banks was substantially worse on average than the

22. The difference of means tests are generated from random effects regressions that pool the quarterly data from the two columns being compared. These regressions are specified as $X_{it} = a + b * D_{it} + u_i + e_{it}$, where X_{it} is the variable being tested, D_i is a dummy equal to 1 for banks in the second of the two pooled samples, u_i is a random disturbance specific to each bank and constant across time, and e_{it} is a random disturbance term with mean zero. The estimated magnitude of b provides the test of economic significance (note that this estimate is usually very similar to the simple difference between the two means being compared) and the statistical difference of b from zero provides the test of statistical significance.

TABLE 2 Summary Statistics for Quarterly Data, 1997:Q2–2001:Q2

	[1] Established Banks ($N = 48{,}146; K = 3{,}777$)		[2] Benchmark Banks ($N = 4{,}667; K = 644$)		[3] Internet-Only Banks ($N = 75; K = 12$)		[4] Internet-Only Banks, Survivor Sample ($N = 49; K = 8$)	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Performance Ratios:								
ROA	.0109	.0098	−.0134***	.0269	−.0431***	.0469	−0.0240	.0347
ROE	.1187	.0967	−.0467***	.1234	−.1842***	.2014	−0.1111***	.1599
SPREAD	.0548	.0140	.0424***	.0163	.0178***	.0178	.0125***	.0170
LOANRATE	.0906	.0115	.0807***	.0159	.0629***	.0181	.0586***	.0174
DEPRATE	.0358	.0081	.0383***	.0101	.0451***	.0123	.0461***	.0121
LOANS	.6141	.1460	.5740***	.1927	.4718*	.2574	.5594	.2511
DEPOSITS	.8450	.0843	.7750***	.1301	.6958*	.1620	.7124	.1739
FEES	.0108	.0157	.0071***	.0169	.0035	.0035	.0031	.0036
NIEXP	.0349	.0193	.0520***	.0323	.0801***	.0663	.0530	.0461
LABOREXP	.0181	.0096	.0259***	.0161	.0293	.0253	.0219	.0250
FTES	.0004	.0002	.0005***	.0003	.0004	.0003	.0003**	.0003
WAGE ($1,000)	$43.54	$13.41	$54.87***	$16.83	$73.05***	$19.56	$70.90***	$15.17
PREMEXP	.0053	.0031	.0085***	.0060	.0134***	.0130	.0089	.0107
OTHEREXP	.0029	.0029	.0044***	.0042	.0091***	.0094	.0055	.0048
OVERHEAD	.0198	.0133	.0356***	.0300	.0213	.0245	.0143	.0238
EQUITY	.0979	.0408	.1909***	.1232	.2329	.1549	.2144	.1575
GROWTH	.0426	.3927	.5339***	.8371	1.0539***	1.5525	1.2357***	1.7416
BADLOANS	.0096	.0116	.0017***	.0067	.0028	.0085	.0007	.0016

Descriptive Variables:								
AGE (quarters)	244.24	150.58	4.81***	2.75	4.29	2.72	4.37	2.83
ASSETS ($1,000)	$192,039	$193,254	$48,668***	$48,610	$221,661***	$256,278	$251,724***	$297,884
%REALESTATE	.6580	.1918	.6245***	.2100	.7511**	.2210	.8130***	.1768
%BUSINESS	.1994	.1475	.2744***	.1803	.0654***	.0941	.0415***	.0582
%CONSUMER	.1284	.1217	.0890***	.1148	.1408	.1552	.0927	.1086
%CREDITCARD	.0053	.0136	.0048**	.0164	.0427***	.0652	.0140	.0227
ALLOWANCE	.0080	.0045	.0065***	.0035	.0033***	.0032	.0042**	.0033
MBHC	.2413	.4279	.1727***	.3780	.0533	.2262	.0000	.0000
THRIFT	.1152	.3193	.0812**	.2732	.6267***	.4869	.6122***	.4923
OCC	.2657	.4417	.2008***	.4006	.0667	.2511	.0000	.0000
JOBGROWTH	.0055	.0039	.0052***	.0043	.0180***	.0076	.0186***	.0076

NOTE.—Definitions: ROA = return on assets (annualized). ROE = return on book equity (annualized). SPREAD = LOANRATE minus DEPRATE. LOANRATE = interest and fees received on loans divided by total loans (annualized). DEPRATE = interest paid on deposits divided by total deposits (annualized). LOANS= total loans divided by total assets. DEPOSITS = total deposits divided by total assets. FEES= noninterest income divided by total assets (annualized). NIEXP = total noninterest expense divided by total assets (annualized). LABOREXP = salary and benefits expense divided by total assets (annualized). FTES = number of full-time-equivalent employees divided by total assets. WAGE = salary and benefits expense divided by FTES (annualized). PREMEXP = expense on premises and equipment divided by total assets (annualized). OTHEREXP = all "other" (i.e., nonlabor and nonpremises) noninterest expenses divided by total assets (annualized). OVERHEAD = book value of physical assets divided by total assets. EQUITY = book value of equity divided by total assets. GROWTH = asset growth rate (annualized). BADLOANS= nonperforming loans divided by total assets. AGE = number of full calendar quarters since the bank's ledger was opened. ASSETS = total assets. %REALESTATE = real estate loans divided by total loans. %BUSINESS = commercial and industrial loans divided by total loans. %CONSUMER = consumer loans divided by total loans. %CREDITCARDS = credit card loans divided by total loans. ALLOWANCE = allowance for loan and lease losses divided by total assets. MBHC = 1 if bank is an affiliate in a multibank holding company; = 0 otherwise. OCC = 1 if bank holds a national bank charter; = 0 otherwise. THRIFT = 1 if bank holds a thrift charter; = 0 otherwise. JOBGROWTH = growth rate of total employment in the bank's home state (annualized).

N refers to the number of quarterly observations, and *K* refers to the number of banks. The superscripts ***, **, and * indicate that the mean value in question is significantly different from the mean value in one of the other columns (col. 2 means are compared to col. 1 means, col. 3 means are compared to col. 2 means, and col. 4 means are also compared to col. 2 means) at the 1%, 5%, and 10% levels. The significance tests are generated from random effects regressions that pool the quarterly data from the two columns being compared. The regressions are specified as $X_{it} = a + b * D_{it} + u_i + e_{it}$, where X_{it} is the variable being tested, D_i is a dummy equal to 1 for banks in the second of the two pooled samples, u_i is a random disturbance specific to each bank and constant across time, and e_{it} is a random disturbance term with mean zero. The statistical significance of the estimate for b provides the test. All variables are in 2000 dollars. Financial ratios that are based on quarterly flows have been converted to annualized values. All variables were truncated at the .005 and .995 percentiles of their sample distributions to eliminate the influence of extreme outliers on the tests.

financial performance of small established banks. On average, return on assets (ROA) and return on equity (ROE) at the branching startups fell short of established bank levels by more than 200 basis points and 700 basis points, respectively. This is strong evidence of a negative financial performance gap between new branching banks and small established banks, consistent with line segment *AB* in figure 1.

Nearly all aspects of branching startup performance contributed to these earnings gaps. Interest margins (SPREAD) averaged 124 basis points lower, due to both lower interest rates charged to borrowers (LOANRATE) and higher interest rates paid to depositors (DEPRATE). The branching startups had difficulty generating business volume, as evidenced by lower levels of loans to assets (LOANS), deposits to assets (DEPOSIT*S*), and noninterest income to assets (FEES). The ratio of noninterest expenses to assets (NIEXP) was 171 basis points higher than at the small established banks, and all three components of noninterest expenses were significantly higher as well: labor expenses to assets (LABOREXP), premises expenses to assets (PREMEXP), and "other" noninterest expenses to assets (OTHEREXP). The higher labor expenses were driven both by higher average wage levels (WAGE) and higher levels of full-time employees to assets (FTES). It is important to note, however, that high levels of noninterest costs at newly chartered banks are more likely to indicate initial excess capacity rather than managerial inefficiency, as evidenced by the high ratio of physical plant to assets (OVERHEAD).

Three performance ratios were better at the newly chartered branching banks than at the small established banks. Equity capital to assets (EQUITY) was twice as large; these capital cushions are crucial to fuel the fast asset growth rates (GROWTH) and absorb the negative earnings typical of new bank startups. Finally, the ratio of nonperforming loans to total loans (BADLOANS) was near zero for the startups because new banks typically hold portfolios of new, unseasoned credits.

By definition, branching startup banks were considerably younger (AGE) and smaller (ASSETS) than small established banks. The startup banks' loan portfolios were more heavily weighted toward commercial loans (%BUSINESS) and less heavily weighted toward real estate loans (%REALESTATE), consumer loans (%CONSUMER), and credit card loans (%CREDITCARD), reflecting the small business orientation of many newly chartered banks.[23] The low level of loan loss reserves to assets (*ALLOWANCE*) for the startup banks is consistent with their low levels of nonperforming loans. Compared to small established banks, the startup banks were more likely to hold state bank charters (i.e., less likely to hold national bank charters [OCC] or thrift charters [THRIFT])

23. DeYoung, Goldberg, and White (1999) find that this focus on small business lending diminishes over time and is virtually absent by the time a bank becomes 20 years old.

and less likely to be affiliates in multibank holding companies (MBHC). Economic conditions, measured by the quarterly state employment growth rate (JOBGROWTH), were weaker in the states in which the new branching banks started up, although this difference was not economically significant.

B. Internet-Only Startups (Col. 3) Relative to Branching Startups (Col. 2)

Profitability at the typical Internet-only startup bank was lower than the already poor profitability at the typical branching startup bank; on average, ROA and ROE were about 300 and 1,400 basis points lower, respectively. These negative performance gaps are consistent with line segment *BC* in figure 1. A closer look at the components of profitability indicates that these banks successfully applied some elements of the Internet-only business model, such as low interest margins and fast asset growth, but did not successfully apply other elements of the model, such as low overhead ratios.

Interest margins at Internet-only start-ups were about 250 basis points lower than at branching startups, due to both lower loan interest rates (178 basis points) and higher deposit interest rates (68 basis points). But, despite offering more attractive prices, the Internet-only startups generated fewer loans (LOANS was about 10 percentage points lower) and attracted fewer deposits (DEPOSITS was about 8 percentage points lower) than the branching startups.[24] The composition of the loan portfolio at the average Internet-only startup was also substantially different, heavy on the transactions loans (%REALESTATE was about 13 percentage points higher, %CONSUMER was about 5 percentage points higher, and %CREDITCARD was about 4 percentage points higher) and light on the relationship loans (%BUSINESS was about 21 percentage points lower) relative to the average branching startup. The low levels of loan generation, deposit generation, and relationship loans are all consistent with the arm's-length nature of banking without branch offices. Mortgages, auto loans, credit cards, and other transactions loans can be underwritten using automated underwriting techniques easily deployed over the Internet, but relationship lending to small businesses requires person-to-person contact. On the positive side, these data suggest that Internet-only startups may have access to larger scale economies than branching startups, because transactions lending techniques have low ratios of variable costs to fixed costs.

Because there is no good single measure of "bank overhead," testing whether Internet-only banks operate with less overhead than branching banks must consider a variety of different financial ratios, including

24. These loan rate and deposit rate comparisons do not control for differences in portfolio composition or risk levels across the two sets of banks. Controls for these phenomena are included in the regression tests.

NIEXP, PREMEXP, OTHEREXP, OVERHEAD, and FTES.[25] The overall evidence suggests that overhead spending is no lower at Internet-only banks. Total noninterest expense ratios were higher by 281 basis points, driven primarily by expenses on physical premises (about one-and-a-half times higher than at the branching startups) and expenses on "other" noninterest items (about twice as high as at the branching startups). The latter category includes items on which Internet-only banks may be especially dependent, such as contracts with venders to service and maintain the Web site, payments to ATM networks that provide liquidity services to Internet-only bank customers, and perhaps most important marketing expenditures: branching banks receive "free" advertising whenever a potential customer walks or drives past a bank branch, but Internet-only banks that exist only in cyberspace have to purchase advertising to attract new customers to the Web site.[26] The significant difference of means for WAGE provides another example of the different mixes of inputs required by these two groups of banks: the average Internet-only bank paid $18,000 more in salary and benefits per worker per year, suggesting that this business model requires a more highly skilled workforce.

The average Internet-only startup was about 45 days younger than the average branching startup, but it was four times larger—a direct result of 100% faster annual asset growth. Rapid growth is easier for transactions-based lenders (e.g., home mortgages) that need not build relationships with their customers; moreover, the low default rates associated with portfolios dominated by home mortgage loans allows these banks to hold significantly lower reserves for bad loans. Internet-only banks serve a nationwide market, so JOBGROWTH was set equal to the national employment growth rate for these banks. Therefore, the JOBGROWTH data are consistent with two possibilities: the Internet-only observations come disproportionately from quarters in which the national economy was performing relatively well or the branching banks tended to start up in states with below-average rates of employment growth.

These data indicate that the financial performance of the typical Internet-only startup fell short of the typical branching startup and that

25. Among the reasons making it difficult to measure relative expenditures on bank overhead are these: Some banks purchase office space (which gets capitalized and then depreciated) while other banks rent it (which gets directly expensed), but depreciation on plant and equipment is not reported as a separate expense line in bank regulatory financial databases.

26. Although regulatory financial data do not systematically break down "other noninterest expenses" into subcategories, secondary records for commercial banks suggest that marketing expenditures constitute a substantial portion of these expenses. (These secondary data are not collected from thrifts.) For the final full year in the data, 60% (three out of five) of the Internet-only commercial bank startups reported that expenditures on "marketing," "advertising," or promotions accounted for at least 10% of their "other noninterest expenses." This contrasts with 31% (or 167 out of 533) of the branching commercial bank startups.

the Internet-only banking model has not performed as originally expected. But these univariate comparisons only offer preliminary evidence. A more thorough investigation asks two additional questions: (1) Can some subset of well-managed banks make the Internet-only model work more profitably? (2) Does increased experience or increased scale materially improve the performance of the Internet-only model? The remainder of Section VI addresses these two questions using simple univariate and bivariate analyses. Sections VII and VIII address these two questions using a more elegant multivariate regression framework.

C. "Surviving" Internet-Only Startups (Col. 4) Relative to Branching Startups (Col. 2)

The results so far indicate that the average Internet-only startup performed poorly relative to the average branching bank startup. But this evidence does not necessarily constitute an indictment of the Internet-only business strategy, rather, it may be that this innovative business model is difficult for the average banker to execute effectively. A better test of the viability of the Internet-only banking model is whether some banks (as opposed to the average bank) have been able to successfully operationalize this strategy. One might argue that the eight Internet-only startup banks in the "survivor" sample—that is, startup banks that were still actively pursuing the Internet-only strategy at the close of the sample period—have been better able to operationalize this business strategy.

Indeed, the ROA performance gap for the eight surviving Internet-only banks was not statistically different from zero, and the ROE performance gap for these banks was relatively small at just 644 basis points. Greater output generation (LOANS and DEPOSITS) accounts for some of this improved performance, but most of it appears to have resulted from basic cost control. Each of the three major categories of noninterest expenses (LABOREXP, PREMEXP, OTHEREXP) was comparable to expense levels at the branching startup banks. Among the indicators of overhead spending, PREMEXP was economically and statistically similar to the branching startup banks, OVERHEAD was economically but not statistically lower than at the branching startups, and FTES was economically and statistically lower than at the branching startups.

These data suggest that banks that implement each of the primary elements of the Internet-only business model early in their lives (lower overhead, more attractive prices, and faster growth), and manage to keep their expenses down, have been more successful. However, these relatively successful Internet-only startups still earned lower returns on equity than the average branching startup bank. Does this profitability gap disappear as well-managed Internet-only banks grow older and gain

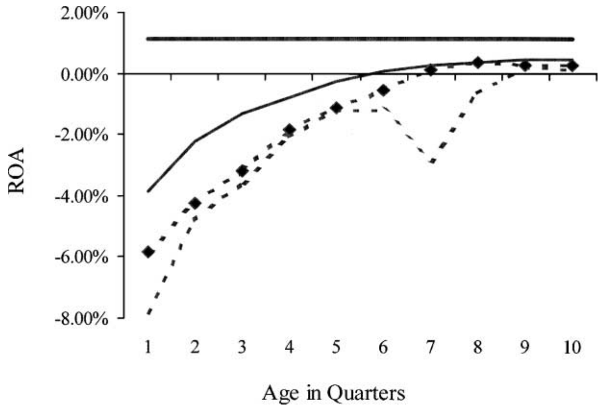

FIG. 2.—Time paths for return on assets (ROA). Quarterly data are drawn from 1997:Q2–2001:Q2 and annualized. The thick solid line is the median ROA for small established banks over 1997:Q2–2001:Q2. The thin solid line is the median quarterly ROA for the newly chartered branching bank sample. The dashed line with diamonds is the median quarterly ROA for the newly chartered Internet-only survivor bank sample. The dashed line without diamonds is the median quarterly ROA for the newly chartered Internet-only bank sample.

experience with the new business model? As they grow larger and capture potential scale economies?

D. Preliminary Evidence of Experience Effects and Scale Effects

Figure 2 maps out ROA time paths for the full 12-bank Internet-only sample and for the 8-bank Internet-only survivor sample. The figure also includes two performance benchmarks: the ROA time path for the branching start-up banks and the average level of ROA for the small established banks. All the performance time paths plot the median (annualized) ROA in each quarter for the banks in question. Consistent with the data in table 2, the Internet-only time path lies below the branching bank time path, with the time path for the Internet-only survivors in between. Consistent with the stylized figure 1, the Internet-only time paths have steeper slopes than the branching bank time path, crude evidence of technology-based experience effects. For the Internet-only survivors, the ROA performance gap diminishes from about 200 basis points for 1-quarter-old banks to about 100 basis points for 5-quarter-old banks and finally to less than 50 basis points for 7- to 10-quarter-old banks.

Figure 3 similarly maps out ROA size paths, where bank size is measured discretely along the horizontal axis in nine asset size categories.[27] These performance size paths exhibit the same relative ordering as the ROA time paths in figure 2. The ROA for Internet-only banks is well

27. The break points between the nine asset size categories are $25 million, $50 million, $75 million, $100 million, $150 million, $200 million, $250 million, and $300 million.

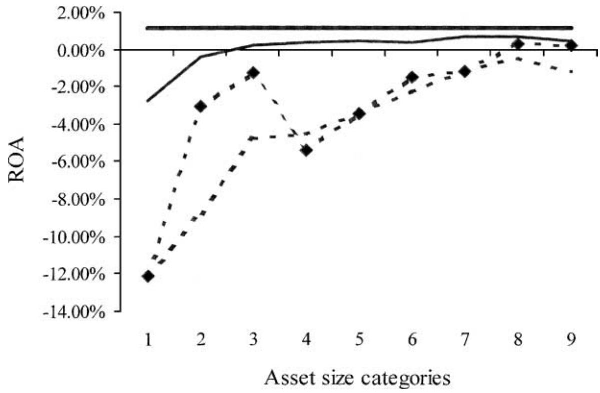

FIG. 3.—Size paths for return on assets (ROA). Quarterly data are drawn from 1997:Q2–2001:Q2 and annualized. The break points between the nine asset size categories are and \$25 million, and \$50 million, and \$75 million, and \$100 million, and \$150 million, and \$200 million, and \$250 million, and and \$300 million. The thick solid line is the median ROA for small established banks over 1997:Q2–2001:Q2. The thin solid line is the median quarterly ROA for the newly chartered branching bank sample. The dashed line with diamonds is the median quarterly ROA for the newly chartered Internet-only survivor bank sample. The dashed line without diamonds is the median quarterly ROA for the newly chartered Internet-only bank sample.

below that for branching banks for the smallest banks (by about 1,000 basis points in the smallest size category), but this performance gap diminishes for larger banks and is virtually nonexistent for the Internet-only survivors in the largest size category. Thus, the figure provides crude evidence of technology-based scale effects. The patterns in figures 2 and 3 are similar because de novo bank age and de novo bank size are closely related (the linear correlation between AGE and ASSETS is a statistically significant 0.549 for the Internet-only banks), and this makes it difficult to know whether technology-based scale effects, technology-based experience effects, or both are responsible for the diminishing ROA performance gaps. The multiple regression tests presented and estimated in the next two sections attempt to identify and discern between these two performance processes.

VII. Regression Framework

Two types of regressions tests are performed here. A static regression analysis tests for the existence and magnitude of cross-sectional financial performance gaps between the Internet-only startup banks and the branching startup banks, controlling for bank age, bank size, and other exogenous influences on bank performance. Equations (1) and (2) specify the static regression tests. A dynamic regression analysis tests for the existence of general and technology-based experience and scale effects, again controlling for exogenous influences on bank performance. Equation (3) specifies the dynamic regression tests. The regressions use pooled data sets that combine the Internet-only startup samples with the branching bank startup sample, and are estimated using both ordinary least squares (OLS) estimation techniques and restricted maximum likelihood (REML) estimation techniques with random effects. Equation (1) is specified as follows:

$$\begin{aligned}
\text{PERFORMANCE}_{i,t} &= \alpha + \beta * \text{INTERNET}_i \\
&+ \delta * \ln\text{AGE}_{i,t} + \lambda * \ln\text{ASSETS}_{i,t} \\
&+ \theta_1 * \%\text{BUSINESS}_{i,t} + \theta_2 * \%\text{REALESTATE}_{i,t} \\
&+ \theta_3 * \text{LOANS}_{i,t} + \theta_4 * \text{ALLOWANCE}_{i,t} \\
&+ \theta_5 * \text{MBHC}_i + \theta_6 * \text{THRIFT}_i + \theta_7 * \text{OCC}_i + \theta_8 * \text{JOBGROWTH}_{i,t} \\
&+ \theta_9 * \text{YEAR}_t + \theta_{10} * \text{QUARTER}_t + \varepsilon_{i,t}, \qquad (1)
\end{aligned}$$

where PERFORMANCE can be any one of the 18 financial performance ratios displayed in the top panel in table 2. The subscript i indexes bank-level observations, and the subscript t indexes time in quarters. INTERNET is a dummy variable equal to 1 for Internet-only startup banks, and the coefficient β provides the main static test. A statistically significant value for β indicates a financial performance gap between the Internet-only startups and the branching bank startups at the means of the data.

In these static regression tests, both AGE and ASSETS are characterized as control variables. The natural log of AGE is included to control for the effects of accumulated production experience on bank performance, and the natural log of ASSETS is included to control for the effects of operating scale on bank performance.[28] The terms %BUSINESS and %REALESTATE are included to control for the effects of loan portfolio mix on bank input requirements, bank earnings, bank growth rates, and other bank performance measures. LOANS and ALLOWANCE are standard measures of bank riskiness.[29] MBHC, THRIFT, and OCC are dummy variables equal to 1 for banks that, respectively, are affiliates in multibank holding companies, hold thrift charters, and hold national bank charters. JOBGROWTH is included to control for economic conditions in the home state of bank i during quarter t. (The nationwide quarterly average is assigned to the Internet-only banks.) YEAR and QUARTER are

28. AGE is specified in natural logs because previous research (as well as the crude time paths displayed in figure 2) found that most measures of de novo bank financial performance approach established bank levels at a decreasing rate over time (e.g., DeYoung 1999). ASSETS is specified in natural logs because marginal gains from scale economies tend to decrease with bank size.

29. LOANS is excluded from the regressions in which it is the dependent performance variable.

dummy variables that control for cyclical and seasonal influences on bank performance not captured by the other control variables. The structure of the disturbance term $\varepsilon_{i,t}$ depends on whether OLS or REML techniques are used to estimate the regression equations (details later).

Given the small number of banks in the Internet-only sample, the estimates of β in equation (1) could be influenced by outlying observations. To account for this possibility, equation (2) replaces the single Internet-only term with a vector of individual Internet-only bank dummies as follows:

$$\begin{aligned}\text{PERFORMANCE}_{i,t} &= \alpha + \sum_{j=1}^{12} \beta_j * \text{INTERNET}_{ij} \\ &+ \delta * \text{lnAGE}_{i,t} + \lambda * \text{lnASSETS}_{i,t} \\ &+ \theta_1 * \%\text{BUSINESS}_{i,t} + \theta_2 * \%\text{REALESTATE}_{i,t} \\ &+ \theta_3 * \text{LOANS}_{i,t} + \theta_4 * \text{ALLOWANCE}_{i,t} \\ &+ \theta_5 * \text{MBHC}_i + \theta_6 * \text{THRIFT}_i + \theta_7 * \text{OCC}_i + \theta_8 * \text{JOBGROWTH}_{i,t} \\ &+ \theta_9 * \text{YEAR}_t + \theta_{10} * \text{QUARTER}_t + \varepsilon_{i,t}, \qquad (2)\end{aligned}$$

which essentially provides an individual intercept shift for each of the 12 Internet-only banks. The aggregate number of positive and negative β_j coefficients in equation (2) serves as a check on whether the results for β in equation (1) are systematic. Both parametric and nonparametric tests of significance are used to make this determination.

Equations (1) and (2) assume away technology-based experience effects and technology-based scale effects because they restrict the Internet-only banks to follow the same performance time path (δ * lnAGE) and the same performance size path (λ * lnASSETS) as the branching banks. Equation (3) allows for dynamic tests of Internet-only bank performance by relaxing these restrictions:

$$\begin{aligned}\text{PERFORMANCE}_{i,t} &= \alpha + \beta * \text{INTERNET}_i \\ &+ \delta * \text{lnAGE}_{i,t} + \lambda * \text{lnASSETS}_{i,t} \\ &+ \gamma * \text{INTERNET}_i * \text{lnAGE}_{i,t} + \eta * \text{INTERNET}_i * \text{lnASSETS}_{i,t} \\ &+ \theta_1 * \%\text{BUSINESS}_{i,t} + \theta_2 * \%\text{REALESTATE}_{i,t} \\ &+ \theta_3 * \text{LOANS}_{i,t} + \theta_4 * \text{ALLOWANCE}_{i,t} \\ &+ \theta_5 * \text{MBHC}_i + \theta_6 * \text{THRIFT}_i + \theta_7 * \text{OCC}_i + \theta_8 * \text{JOBGROWTH}_{i,t} \\ &+ \theta_9 * \text{YEAR}_t + \theta_{10} * \text{QUARTER}_t + \varepsilon_{i,t}. \qquad (3)\end{aligned}$$

The coefficients on lnAGE, INTERNET * lnAGE, lnASSETS, and INTERNET * lnASSETS provide the main dynamic tests. The coefficient δ

gives the slope of the performance time path for branching startups (general experience effects); the sum $\delta + \gamma$ gives the slope of the performance time path for Internet-only startups (general experience effects plus technology-based experience effects); and the magnitude and statistical significance of γ indicates the importance of any technology-based experience effects. Similarly, the coefficient λ gives the slope of the performance size path for branching startups (general scale effects); the sum $\lambda + \eta$ gives the slope of the performance size path for Internet-only startups (general scale effects plus technology-based scale effects); and the magnitude and statistical significance of η indicates the importance of any technology-based scale effects. All these effects are estimated at the means of the data.

Empirically separating technology-based experience effects from technology-based scale effects may be difficult, given the relatively small number of observations for Internet-only startup banks as well as the strong correlation between AGE and ASSETS for all newly chartered banks. Robustness tests of equation (3) that exclude either the INTERNET * lnAGE term or the INTERNET * lnASSETS term are performed to investigate the potential effects of colinearity on the parameter estimates.

As stated earlier, all the regressions are estimated using OLS and REML techniques with random effects. The random effects approach includes a bank-specific random disturbance term (in addition to the usual random disturbance term) that accounts for unexplained variation in the dependent variable that is specific to bank *i* during the sample period. Because the true form of this bank-specific variation is unknown, four alternative structures are used to model the variance-covariance matrix, the details of which are presented in the appendix. Note that a fixed effects estimation approach is not feasible here, because the phenomena being tested for are themselves fixed effects. For example, the coefficients β_j in equation (2) are bank fixed effects. Furthermore, much of the variation necessary to estimate the coefficients β, γ, and η in equations (1) and (3) would be soaked up in a bank fixed-effects model.

VIII. Regression Results

Selected regression results for equations (1), (2), and (3) are displayed in tables 3 through 6. These estimates reflect the financial performance of the average new startup bank in the data, which was about 1¼ years old. Because regression coefficients are estimated with error, the estimated coefficients β_1 through β_{12} in equation (2) are analyzed as a group and not separately identified by the names of the 12 Internet-only startup banks. Complete results for the ROA regressions are presented in the appendix; complete results for the regressions using the other 17 dependent variables are available on request from the author.

TABLE 3 Estimates of β from 180 Regressions of Equation (1)

Dependent Variable	Data Set	OLS Regressions	Random Effects Model Model 1	Model 2	Model 3	Model 4	Average
ROA	Full	−.0399***	−.0423***	−.0468***	−.0474***	−.0293***	−.0411
	Survivors	−.0251***	−.0312***	−.0319***	−.0339***	−.0163***	−.0277
ROE	Full	−.1904***	−.1960***	−.1960***	−.2004***	−.1929***	−.1951
	Survivors	−.1317***	−.1520***	−.1321***	−.1351***	−.1299***	−.1362
SPREAD	Full	−.0187***	−.0177***	−.0162***	−.0165***	−.0169***	−.0172
	Survivors	−.0245***	−.0230***	−.0204***	−.0214***	−.0210***	−.0221
DEPRATE	Full	.0079***	.0047**	.0061***	.0057**	.0058**	.0060
	Survivors	.0068***	.0051*	.0059**	.0055**	.0059**	.0058
LOANRATE	Full	−.0121***	−.0124***	−.0111***	−.0112***	−.0099***	−.0113
	Survivors	−.0177***	−.0174***	−.0160***	−.0162***	−.0145***	−.0164
DEPOSITS	Full	−.0854***	−.1317***	−.1474***	−.1473***	−.1667***	−.1357
	Survivors	−.0878***	−.1357***	−.1608***	−.1637***	−.1648***	−.1426
LOANS	Full	−.0699***	−.0261	.0726	.0702	.0941**	.0282
	Survivors	−.0081	.0364	.1436***	.1410***	.1897***	.1005
FEES	Full	−.0092***	−.0051	−.0057	−.0058	−.0027	−.0057
	Survivors	−.0098***	−.0056	−.0059	−.0061	−.0024	−.0060
NIEXP	Full	.0336***	.0500***	.0576***	.0569***	.0370***	.0470
	Survivors	.0118***	.0363***	.0399***	.0420***	.0305***	.0321
PREMEXP	Full	.0067***	.0088***	.0091***	.0095***	.0091***	.0086
	Survivors	.0029***	.0068***	.0064***	.0073***	.0046***	.0056
LABOREXP	Full	.0084***	.0189***	.0212***	.0216***	.0143***	.0169
	Survivors	.0025	.0166***	.0179***	.0189***	.0109**	0.0134
OTHEREXP	Full	.0042***	.0048***	.0053***	.0051***	.0025***	.0044
	Survivors	.0015**	.0026**	.0027***	.0028**	.0019**	.0023
FTES	Full	.00007**	.00025***	.00029***	.00028***	.00024***	0.00023
	Survivors	.00000	.00024***	.00029***	.00029***	.00027**	.00022
WAGE	Full	8.9940***	12.7257***	12.3029***	12.9293***	12.3018***	11.8507
	Survivors	8.1357***	11.2089**	10.8547**	11.4685**	9.3700*	10.2076

TABLE 3 ***(Continued)***

Dependent Variable	Data Set	OLS Regressions	Random Effects Model: Model 1	Model 2	Model 3	Model 4	Average
GROWTH	Full	.3347***	.2464**	.2984***	.2531	.0915	.2448
	Survivors	.6585***	.6858***	.6550***	.7835***	.5307**	.6627
EQUITY	Full	.0840***	.1550***	.1828***	.1866***	.1468***	.1510
	Survivors	.0854***	.1652***	.2078***	.2212***	.1719***	.1703
OVERHEAD	Full	.00101	.01744**	.02498***	.02556***	.02382***	.01856
	Survivors	−.00240	.02010**	.02810***	.02840***	.02900***	.02064
BADLOANS	Full	.0009	.0000	.0009	.0008	−.0015	.0002
	Survivors	−.0013	−.0024	−.0018	−.0018	−.0016	−.0018

NOTE.—The superscripts ***, **, and * indicate the coefficient is statistically different from zero at the 1%, 5%, and 10% levels. The average is the unweighted mean of the five coefficient estimates in each row.

TABLE 4 Numbers of Positive and Negative Estimates of $\sum_{j=1}^{12} \beta_j$ from 90 Regressions of Equation (2)

			Random Effects Model			
Dependent Variable	Coefficient Signs	OLS Regressions	Model 1	Model 2	Model 3	Model 4
ROA	Positive and significant	0	0	0	0	0
	Negative and significant	9	8	8	8	6
	Most frequent sign	12 negative***	12 negative***	12 negative***	12 negative***	11 negative***
ROE	Positive and significant	0	0	0	0	0
	Negative and significant	9	8	8	7	7
	Most frequent sign	12 negative***	11 negative***	12 negative***	12 negative***	12 negative***
SPREAD	Positive and significant	0	0	0	0	0
	Negative and significant	10	3	3	3	5
	Most frequent sign	11 negative***	11 negative***	11 negative***	11 negative***	10 negative***
DEPRATE	Positive and significant	7	2	2	2	2
	Negative and significant	0	0	0	0	1
	Most frequent sign	10 positive***	8 positive*	10 positive***	10 positive***	10 positive***
LOANRATE	Positive and significant	0	0	0	0	0
	Negative and significant	7	4	4	4	4
	Most frequent sign	10 negative***	9 negative***	9 negative***	9 negative***	10 negative***
DEPOSITS	Positive and significant	1	0	0	0	0
	Negative and significant	7	3	3	5	6
	Most frequent sign	10 negative***	10 negative***	10 negative***	10 negative***	10 negative***
LOANS	Positive and significant	3	1	2	2	4
	Negative and significant	5	3	1	1	2
	Most frequent sign	7 negative	7 negative	8 positive*	8 positive*	9 positive**
FEES	Positive and significant	0	0	0	0	0
	Negative and significant	4	0	0	0	0
	Most frequent sign	11 negative***	11 negative***	11 negative***	11 negative***	10 negative***

TABLE 4 (***Continued***)

Dependent Variable	Coefficient Signs (no.)	OLS Regressions	Random Effects Model			
			Model 1	Model 2	Model 3	Model 4
NIEXP	Positive and significant	6	6	8	8	7
	Negative and significant	1	0	0	0	0
	Most frequent sign	9 positive***	11 positive***	11 positive***	11 positive***	10 positive***
PREMEXP	Positive and significant	5	3	5	5	3
	Negative and significant	1	0	0	0	0
	Most frequent sign	10 positive***	10 positive***	10 positive***	10 positive***	10 positive***
LABOREXP	Positive and significant	4	4	3	3	2
	Negative and significant	1	0	0	0	0
	Most frequent sign	7 positive	11 positive***	11 positive***	11 positive***	10 positive***
OTHEREXP	Positive and significant	5	4	4	4	3
	Negative and significant	0	0	0	0	0
	Most frequent sign	8 positive*	11 positive***	10 positive***	10 positive***	9 positive**
FTES	Positive and significant	3	2	4	4	2
	Negative and significant	1	0	0	0	0
	Most frequent sign	8 positive*	11 positive***	11 positive***	11 positive***	10 positive***

WAGE	Positive and significant	6	2	2	2	2
	Negative and significant	0	0	0	0	0
	Most frequent sign	8 positive*	9 positive**	8 positive*	9 positive**	8 positive*
GROWTH	Positive and significant	4	4	4	3	2
	Negative and significant	2	3	3	3	1
	Most frequent sign	6 positive	6 positive	6 positive	6 positive	7 negative
EQUITY	Positive and significant	6	6	6	5	4
	Negative and significant	2	0	0	0	0
	Most frequent sign	9 positive**	10 positive***	10 positive***	11 positive***	10 positive***
OVERHEAD	Positive and significant	2	2	2	4	3
	Negative and significant	3	0	0	0	0
	Most frequent sign	7 negative	8 positive*	9 positive**	9 positive**	11 positive***
BADLOANS	Positive and significant	1	1	1	1	0
	Negative and significant	1	0	0	0	0
	Most frequent sign	7 negative	9 negative**	8 negative*	8 negative*	11 negative***

NOTE.—Superscripts ***, **, and * indicate that the probability of observing this many positive or negative coefficients (out of 12) is at most 1%, 5%, or 10%, respectively, in binomial nonparametric tests.

TABLE 5 **Estimated Coefficients for the Terms δ * $\ln AGE_{i,t}$ (General Experience Effects), λ * $\ln ASSETS_{i,t}$ (General Scale Effects), γ * $INTERNET_i$ * $\ln AGE_{i,t}$ (Technology-Based Experience Effects), and η * $INTERNET_i$ * $\ln ASSETS_{i,t}$ (Technology-Based Scale Effects) from 90 Regressions of Equation (3) for the Full Data Set**

			Random Effects Model				
Dependent Variable		OLS Regressions	Model 1	Model 2	Model 3	Model 4	Average
ROA	lnAGE	.0139***	.0122***	.0147***	.0146***	.0159***	.0143
	lnAGE * INB	−.0040	−.0062	−.0080	−.0079	−.0007	−.0053
	lnASSETS	.0111***	.0160***	.0150***	.0160***	.0087***	.0134
	lnASSETS * INB	.0027	.0064	.0082*	.0089*	.0050	.0062
ROE	lnAGE	.0489***	.0447***	.0465***	.0470***	.0493***	.0473
	lnAGE * INB	.0268	.0141	.0068	.0118	.0120	.0143
	lnASSETS	.0419***	.0438***	.0414***	.0408***	.0382***	.0412
	lnASSETS * INB	−.0462***	−.0449**	−.0350	−.0365	−.0325	−.0390
SPREAD	lnAGE	.0073***	.0082***	.0099***	.0093***	.0104***	.0090
	lnAGE * INB	.0020	−.0022	.0000	.0004	−.0002	.0000
	lnASSETS	−.0022***	−.0015**	−.0007	−.0011	−.0012*	−.0013
	lnASSETS * INB	−.0007	.0009	−.0011	−.0020	−.0004	−.0007
DEPRATE	lnAGE	.0023***	.0037***	.0038***	.0040***	.0038***	.0035
	lnAGE * INB	−.0023	.0041**	−.0008	.0000	−.0002	.0001
	lnASSETS	.0011***	.0022***	−.0007*	.0002	.0000	.0006
	lnASSETS * INB	.0043***	−.0018	.0062***	.0054***	.0050***	.0038
LOANRATE	lnAGE	.0096***	.0112***	7.0117***	.0121***	.0120***	.0113
	lnAGE * INB	−.0003	.0011	−.0007	.0010	.0018	.0006
	LnASSETS	−.0011***	.0002	−.0007	−.0003	−.0013**	−.0006
	lnASSETS * INB	.0036**	.0004	.0041	.0019	.0007	.0021
DEPOSITS	lnAGE	.0614***	.0528***	.0657***	.0660***	.0772***	.0646
	lnAGE * INB	−.0697***	−.0904***	−.0090	−.0020	.0398	−.0262
	lnASSETS	.0511***	.1188***	.1201***	.1189***	.0794***	.0977
	lnASSETS * INB	−.0014	.0023	−.0606***	−.0649***	−.1356***	−.0520

LOANS	lnAGE	.0742***	.1034***	.1254***	.1254***	.1325***	.1122
	lnAGE * INB	−.0012	.0459*	.0672**	.0679**	.0531	.0466
	lnASSETS	.0176***	−.0006	−.0540***	−.0539***	−.0681***	−.0318
	lnASSETS * INB	−.0132	−.0254	−0.0613**	−0.0613**	−.0161	−.0355
FEES	lnAGE	.0009**	.0008*	.0009	.0009*	.0012**	.0009
	lnAGE * INB	−.0004	−.0012	.0007	.0001	−.0011	−.0004
	lnASSETS	.0009**	.0001	.0001	.0003	−0.0008*	.0001
	lnASSETS * INB	−.0017	.0006	−.0018	−.0011	.0009	−.0006
NIEXP	lnAGE	−.0089***	−.0062***	−.0085***	−.0082***	−.0091***	−.0082
	lnAGE * INB	−.0001	.0020	.0074	.0064	−.0090	.0014
	lnASSETS	−.0150***	−.0287***	−.0283***	−.0297***	−.0225***	−.0248
	lnASSETS * INB	−.0019	−.0102**	−.0167**	−.0152**	.0006	−.0087
PREMEXP	lnAGE	−.0008***	−.0009***	−.0012***	−.0012***	−.0013***	−.0011
	lnAGE * INB	−.0015	.0036***	.0011	.0015	.0014	.0012
	lnASSETS	−.0033***	−.0043***	−.0044***	−.0045***	−.0035***	−.0040
	lnASSETS * INB	.0033***	−.0025**	.0005	−.0003	.0003	.0003
LABOREXP	lnAGE	−.0052***	−.0035***	−.0043***	−.0043***	−.0046***	−.0044
	lnAGE * INB	.0054*	.0108***	.0027	.0027	.0050	.0053
	lnASSETS	−.0078***	−.0150***	−.0154***	−.0161***	−.0121***	−.0133
	lnASSETS * INB	−.0049**	−.0110***	−.0040	−.0038	−.0041	−.0056
OTHEREXP	lnAGE	−.0007***	−.0005***	−.0007***	−.0006***	−.0010***	−.0007
	lnAGE * INB	−.0016**	−.0040***	−.0007	−.0014	−.0053***	−.0026
	lnASSETS	−.0010***	−.0019***	−.0016***	−.0019***	−.0011***	−.0015
	lnASSETS * INB	−.0001	.0011	−.0015*	−.0008	.0018***	.0001
FTES	lnAGE	−.0001***	.0000***	.0000***	.0000***	−.0001***	−.0001
	lnAGE * INB	.0000	.0000	.0000	.0000	−.0001	.0000
	lnASSETS	−.0002***	−.0003***	−.0003***	−.0003***	−.0003***	−.0003
	lnASSETS * INB	.0000	.0000	.0001*	.0001*	.0001**	.0000
WAGE	lnAGE	−3.3409***	−2.6415***	−3.3820***	−2.9128***	−3.1837***	−3.0922
	lnAGE * INB	6.9682**	11.8268***	4.7604	7.2319**	10.6104***	8.2795
	lnASSETS	2.0892***	−.4441	.7016	−.4587	−.1174	.3541
	lnASSETS * INB	−.0172	−6.7058**	.4145	−2.7774	−3.8050	−2.5782

TABLE 5 ***(Continued)***

Dependent Variable		OLS Regressions	Random Effects Model: Model 1	Model 2	Model 3	Model 4	Average
GROWTH	lnAGE	−.6916***	−.6921***	−.6952***	−.6995***	−.6187***	−.6794
	lnAGE * INB	−.0820	−.2795	−.1418	−.2157	−.2755	−.1989
	lnASSETS	.0997***	.1241***	.1254***	.1468***	.1153***	.1223
	lnASSETS * INB	−.3828***	−.3695***	−.3655***	−.3680***	−.2540**	−.3480
EQUITY	lnAGE	−.0613***	−.0467***	−.0532***	−.0517***	−.0658***	−.0558
	lnAGE * INB	.0875***	0.0381**	−.0018	−.0322**	−.1048***	−.0026
	lnASSETS	−.0673***	−.1529***	−.1765***	−.1783***	−.1080***	−.1366
	lnASSETS * INB	−.0319***	.0282**	.0596***	.0954***	.1418***	.0586
OVERHEAD	lnAGE	−.0014*	.0015*	.0019**	.0021**	−.0001	.0008
	lnAGE * INB	−.0118**	−.0060	−.0096**	−.0092**	−.0155***	−.0104
	lnASSETS	−.0126***	−.0190***	−.0257***	−.0272***	−.0213***	−.0212
	lnASSETS * INB	.0205***	.0193***	.0248***	.0247***	.0264***	.0231
BADLOANS	lnAGE	.0009***	.0005**	.0004*	.0004	−0.0002	.0004
	lnAGE * INB	.0027**	.0055***	.0033**	.0035**	.0011	.0032
	lnASSETS	.0003**	.0009***	.0007***	.0007***	.0006***	.0007
	lnASSETS * INB	−0.0022**	−0.0035***	−0.0026*	−0.0026*	−0.0011	−0.0024

NOTE.—The superscripts ***, **, and * indicate the coefficient is statistically different from zero at the 1%, 5%, and 10% levels. The average is the unweighted mean of the five coefficient estimates in each row.

TABLE 6 Estimated Coefficients for the Terms δ * $\ln AGE_{i,t}$ (General Experience Effects), λ * $\ln ASSETS_{i,t}$ (General Scale Effects), γ * $INTERNET_i$ * $\ln AGE_{i,t}$ (Technology-Based Experience Effects), and η * $INTERNET_i$ * $\ln ASSETS_{i,t}$ (Technology-Based Scale Effects) from 90 Regressions of Equation (3) for the Survivor Data Set

			Random Effects Model				
Dependent Variable		OLS Regressions	Model 1	Model 2	Model 3	Model 4	Average
ROA	lnAGE	.0140***	.0122***	.0148***	.0147***	.0154***	.0142
	lnAGE * INB	−.0019	−.0059	−.0073	−.0082	.0017	−.0043
	lnASS	.0112***	.0160***	.0150***	.0159***	.0082***	.0133
	lnASS * INB	.0076**	.0073	.0116**	.0126**	.0012	.0081
ROE	lnAGE	.0495***	.0449***	.0469***	.0473***	.0495***	.0476
	lnAGE * INB	.0335	.0236	.0111	.0164	.0174	.0204
	lnASS	.0421***	.0438***	.0415***	.0403***	.0379***	.0411
	lnASS * INB	−.0168	−.0443*	−.0171	−.0256	−.0247	−.0257
SPREAD	lnAGE	.0072***	.0081***	.0099***	.0093***	.0104***	.0090
	lnAGE * INB	.0013	−.0010	−.0006	.0005	−.0021	−.0004
	lnASS	−.0022***	−.0015**	−.0007	−.0011	−.0012*	−.0013
	lnASS * INB	.0019	.0014	.0008	−.0004	.0032	.0014
DEPRATE	lnAGE	.0023***	.0038***	.0038***	.0041***	.0038***	.0035
	lnAGE * INB	−.0041**	.0014	−.0041	−.0030	−.0037	−.0027
	lnASS	.0012***	.0022***	−.0007**	.0002	.0000	.0006
	lnASS * INB	.0044***	−.0007	.0071***	.0064***	.0058***	.0046
LOANRATE	lnAGE	.0095***	.0111***	.0116***	.0120***	.0120***	.0112
	lnAGE * INB	−.0028	−.0010	−.0042	−.0021	−.0046	−.0029
	lnASS	−.0011***	.0002	−.0007	−.0003	−.0013**	−.0006
	lnASS * INB	.0063***	.0024	.0068**	.0046	.0059*	.0052
DEPOSITS	lnAGE	.0612***	.0528***	.0665***	.0667***	.0780***	.0650
	lnAGE * INB	−.0677***	−.0637**	.0332	.0439*	.0799**	.0051
	lnASS	.0511***	.1197***	.1208***	.1197***	.0787***	.0980
	lnASS * INB	−.0090	−.0163	−.0738***	−.0788***	−.1553***	−.0666

TABLE 6 ***(Continued)***

Dependent Variable		OLS Regressions	Random Effects Model				Average
			Model 1	Model 2	Model 3	Model 4	
LOANS	lnAGE	.0745***	.1039***	.1255***	.1253***	.1323***	.1123
	lnAGE * INB	.0302	.0962***	.1406***	.1420***	.1207***	.1059
	lnASS	.0174***	−.0005	−.0536***	−.0533***	−.0673***	−.0315
	lnASS * INB	−.0444	−.0554**	−.0889***	−.0903***	−.0483	−.0655
FEES	lnAGE	.0009**	.0008*	.0009	.0009*	.0012**	.0010
	lnAGE * INB	−.0003	−.0013	.0000	−.0002	−.0013	−.0006
	lnASS	.0009**	.0001	.0001	.0003	−0.0008*	.0001
	lnASS * INB	−0.0010	.0009	−.0008	−.0005	.0015	.0000
NIEXP	lnAGE	−.0092***	−.0062***	−.0085***	−.0084***	−.0088***	−.0082
	lnAGE * INB	.0011	.0151**	.0061	.0102	.0004	.0066
	lnASS	−.0151***	−.0288***	−.0282***	−.0283***	− .0226***	−.0246
	lnASS * INB	−.0136***	−.0191***	−.0201***	−.0217***	−.0016	−.0152
PREMEXP	lnAGE	−.0008***	−.0008***	−.0012***	−.0011***	−.0014***	−.0011
	lnAGE * INB	−.0035***	.0016	.0002	.0008	−.0007	−.0003
	lnASS	−.0033***	−.0042***	−.0043***	−.0045***	−.0032***	−.0039
	lnASS * INB	.0009	−.0017	−.0001	−.0007	.0002	−.0003
LABOREXP	lnAGE	−.0052***	−.0034***	−.0043***	−.0043***	−.0047***	−.0044
	lnAGE * INB	.0023	.0086**	.0000	−.0001	−.0003	.0021
	lnASS	−.0078***	−.0150***	−.0155***	−.0161***	−.0115***	−.0132
	lnASS * INB	−.0089***	−.0104***	−.0041	−.0039	−.0002	−.0055
OTHEREXP	lnAGE	−.0008***	−.0005***	−.0008***	−.0007***	−.0009***	−.0007
	lnAGE * INB	.0006	.0001	.0014	.0018	−.0007	.0006
	lnASS	−.0010***	−.0019***	−.0016***	−.0019***	−.0012***	−.0015
	lnASS * INB	−.0014**	−.0017**	−.0026***	−.0027***	−.0001	−.0017
FTES	lnAGE	−.0001***	.0000***	.0000***	.0000***	−.0001***	−.0001
	lnAGE * INB	.0000	.0001*	.0000	.0000	.0000	.0000
	lnASS	−.0002***	−.0003***	−.0003***	−.0003***	−.0003***	−.0003
	lnASS * INB	.0000	.0000	.0001	.0001	.0001*	.0000

WAGE	lnAGE	−3.2998***	−2.5543***	−3.3503***	−2.8867***	−3.1921***	−3.0566
	lnAGE * INB	5.9155	4.5379	1.1522	.6207	1.6751	2.7803
	lnASS	2.0871***	−.4388	.6726	−.4489	.0241	.3792
	lnASS * INB	−4.7040*	−3.1572	−1.2002	−.5116	.1160	−1.8914
GROWTH	lnAGE	.2241***	.2051***	.2422***	.4447***	.3436***	.2919
	lnAGE * INB	.2311	.2700	.2260	.3340**	.2772**	.2677
	lnASS	.0221	.0222	0254	.0698***	.0819***	.0443
	lnASS * INB	−.3665***	−.3631***	−.3582***	−.2101**	−.3272***	−.3250
EQUITY	lnAGE	−.0612***	−.0464***	−.0538***	−.0525***	−.0669***	−.0562
	lnAGE * INB	.1020***	.0584***	−.0202	−.0741***	−.1085***	−.0085
	lnASS	−.0674***	−.1539***	−.1779***	−.1797***	−.1092***	−.1376
	lnASS * INB	−.0376***	.0172	.0665***	.1125***	.1386***	.0594
OVERHEAD	lnAGE	−.0015**	.0015*	.0020**	.0022***	−.0001	.0008
	lnAGE * INB	−.0161**	−.0061	−.0085*	−.0080	−.0088	−.0095
	lnASS	−.0126***	−.0190***	−.0258***	−.0273***	−.0214***	−.0212
	lnASS * INB	.0189***	.0194***	.0267***	.0275***	.0230***	.0231
BADLOANS	lnAGE	.0009***	.0005**	.0004*	.0003	−.0002	.0004
	lnAGE * INB	.0007	.0016	.0007	.0009	.0003	.0008
	lnASS	.0003**	.0009***	.0007***	.0007***	.0006***	.0006
	lnASS * INB	−.0009	−.0012	−.0013	−.0013	−.0011	−.0012

Note.—The superscripts ***, **, and * indicate the coefficient is statistically different from zero at the 1%, 5%, and 10% levels. The Average is the unweighted mean of the five coefficient estimates in each row.

A. Static Tests of Performance

Table 3 displays the estimated values of β from 180 regressions of equation (1). These regressions used 18 dependent variables (listed in the first column of table 3), two Internet-only banking data samples (the full sample of 12 banks and the survivor sample of 8 banks), and five estimation procedures (OLS and four random effects approaches).[30] For convenience, the last column in table 3 displays the simple average for the five estimated values of β in each row. The estimates of β are relatively robust to the choice of an estimation technique. In only a few cases (LOANS, FEES, OVERHEAD) did the sign or statistical significance of the OLS β vary systematically from the sign or statistical significance of the random effects values of β, although the OLS estimates of β tended to be smaller in absolute magnitude.

The signs of the estimated β values in table 3 are largely consistent with the performance gaps inferred by the difference of means tests in table 2; however, the performance gaps inferred by the regressions are more often statistically significant and have different magnitudes, because they are conditioned on the exogenous regression variables. On average, across the five estimation techniques, profitability was substantially lower at the Internet-only startups than at the branching startups, by 411 basis points of ROA and by 1,951 basis points of ROE. This profitability gap was driven by deficiencies in a number of performance areas. Interest spreads were lower on average by 172 basis points (about two-thirds due to lower loan interest rates and about one-third due to higher deposit interest rates). Noninterest expenses to assets was 470 basis points higher than at the average branching startup, with labor expenses accounting for the largest portion of this cost disadvantage. The average Internet-only bank paid an estimated $12,000 more in annual salaries and benefits per employee than the average branching bank and hired an estimated 50 more full-time-equivalent employees (.23 employees per million dollars of assets times $220 million in assets). On the plus side, the average Internet-only startup grew about 24 percentage points faster than the average branching startup, and its equity-to-assets ratio was about 15 percentage points higher, almost exactly offsetting its 13.5 percentage point financing shortfall in

30. To conserve space, goodness-of-fit measures are not reported in tables 3 through 6. The statistical fit of the 450 regression equations reported in these tables vary substantially depending on which of the 18 performance variables is used on the left-hand-side of the regression. For example, in the OLS estimations of eq. (1) for the full data set, the three highest adjusted R^2 statistics were .5426 for EQUITY, .4481 for ROA, and .4444 for LOAN, while the three lowest adjusted R^2 statistics were .0523 for GROWTH, .0653 for FEES, and .0693 for WAGE. In 14 of these 18 cases, the adjusted R^2 statistics exceeded .1500, and in 11 of these 18 cases the adjusted R^2 statistics exceeded .2500. In general, adjusted R^2 were slightly larger in the more-flexibly specified eqq. (2) and (3). Although the random effects estimations do not generate a goodness-of-fit statistic directly comparable to adjusted R^2s, the likelihood ratios in these regressions suggest ranges and patterns of statistical fit similar to the OLS regressions.

deposits to assets. No systematically significant performance gaps were associated with nonperforming loans, noninterest income, loans to assets, or physical overhead.

For the Internet-only banks in the survivor data set, these performance gaps tended to be smaller, but they remained statistically significant. For example, the profitability performance gaps averaged just 277 basis points of ROA and 1,362 basis points of ROE for the eight survivor Internet-only banks. This superior financial performance was driven mostly by lower noninterest expenses and, to some extent, larger loan balances and more rapid asset growth.

Table 4 summarizes the signs and statistical significance of the estimated vectors of β_j coefficients from 90 regressions of equation (2). These results demonstrate that the estimated performance gaps reported in table 3 for the average Internet-only startup are not being driven by a few poorly performing outliers. Consistent with the equation (1) results, negative β_j coefficients are significantly more prevalent (based on nonparametric tests) than positive β_j coefficients for ROA, ROE, LOANRATE, DEPOSITS, and SPREAD, and positive β_j coefficients are significantly more prevalent than negative β_j coefficients for EQUITY, DEPRATE, NIEXP, PREMEXP, LABOREXP, OTHEREXP, WAGE, and FTES. Moreover, the nonparametric tests indicate two additional negative performance gaps where none existed in table 3: the Internet-only startups were significantly more likely to have lower noninterest income (FEES) and fewer nonperforming loans (BADLOANS) than the average branching startups. The results suggest that only one of the results from equation (1) was driven by outliers: There is no evidence in table 4 that the growth rates (GROWTH) of the Internet-only startups differed systematically from the growth rates of the branching startup banks.

B. Dynamic Tests of Performance

Tables 5and 6 display the regression coefficients from the key terms in eq. (3): $\delta * \text{lnAGE}_{i,t}$ (general experience effects), $\lambda * \text{lnASSETS}_{i,t}$ (general scale effects), $\gamma * \text{INTERNET}_i * \text{lnAGE}_{i,t}$ (technology-based experience effects), and $\eta * \text{INTERNET}_i * \text{lnASSETS}_{i,t}$ (technology-based scale effects). Table 5 displays estimates from 90 regressions using the full Internet-only sample, and table 6 displays estimates from 90 regressions using the survivor sample.

The results indicate that Internet-only startups have access to significant technology-based scale economies, over and above the significant general scale economies available to all startup banks. As a result, the financial performance gaps at the Internet-only startup banks tended to narrow as these banks grew larger—in terms of figure 3, the size performance paths are steeper for the Internet-only startups than the branching bank startups. These effects were concentrated in just a few aspects of financial performance, most notably in noninterest expenses.

Despite plentiful evidence of general experience effects for startup banks, the results contain little systematic evidence of technology-based learning or experience effects.

General experience effects. There is strong evidence of general experience effects in the data. Both ROA (average $\delta = .0143$) and ROE (average $\delta = .0473$) increase over time as the average startup bank ages, gradually reducing the profitability gap between startup banks and small established banks. Most of the underlying components of bank profits also exhibit general experience effects. All three categories of bank production (LOANS, DEPOSITS, and FEES) increase with bank age, while all six of the variables associated with noninterest expenses (NIEXP, PREMEXP, OTHEREXP, LABOREXP, WAGE, and FTES) decline with bank age. Although both deposit interest rates and loan interest rates increase as new banks age, their combined effect results in a larger interest rate spread. The initially high capital cushions at startup banks are consumed over time by negative earnings and rapid asset growth, although new banks' tremendous rates of asset growth slow down somewhat as they grow older. These results are consistent with the hypothesis that startup banks (regardless of business model) learn to more-efficiently control expenses, manage interest rates, and market their products and services as they accumulate experience over time, holding bank size constant.

General Scale Effects. Even though bank age and bank size are strongly correlated at startup banks (as discussed), the regressions tend to generate statistically significant coefficients on both the general experience effect term $\delta * \ln AGE_{i,t}$ and the general scale effect term $\lambda * \ln ASSETS_{i,t}$. Thus, general scale effects operate separately and independently from general experience effects at newly chartered banks. Both ROA (average $\lambda = .0134$) and ROE (average $\lambda = .0412$) increase with the asset size of the startup banks. Five of the six noninterest expense measures (all but WAGE) and OVERHEAD decline as startup banks grow larger, consistent with spreading fixed and semivariable expenses over greater amounts of output. The results suggest that these cost savings may allow larger startup banks to cut their interest margins (SPREAD) without sacrificing earnings. Similarly, because a larger bank can better diversify its investments, increased size may allow startup banks to economize on expensive equity capital (EQUITY) despite experiencing higher ex post credit risk (BADLOANS). Asset growth and deposit generation also are positively associated with startup bank size. These results are consistent with the hypothesis that increased size gives startup banks (regardless of business model) access to (mainly cost-related) scale economies, holding bank age constant.

Technology-Based Experience Effects. There is little evidence of technology-based experience effects in the data. The coefficient γ on the term $INTERNET_i * \ln AGE_{i,t}$ is not statistically different from zero in any of the ROA and ROE regressions reported in tables 5 and 6. This suggests that the profitability of Internet-only startup banks and branching startup banks improved at the same rate as these banks aged and gained experience. Still, some areas of financial performance (LOANS, OTHEREXP, and OVERHEAD) exhibit statistically significant and relatively systematic "learning curves" in table 5. For example, the LOANS experience effect equals 0.1122 * lnAGE for the average branching bank startup (i.e., a doubling of AGE results in a 7.77 percentage point increase in loans to assets) but equals 0.1122 * lnAGE + 0.0466 * lnAGE for the average Internet-only startup (i.e., a doubling of AGE results in an 11.01 percentage point increase in loans to assets).[31] This suggests that startup banks using the Internet-only technology experience steeper learning curves for loan generation than startup banks that use more traditional technologies.

As discussed earlier, the small number of Internet-only observations ($N = 75$) and the strong correlation between AGE and ASSETS at young banks may make the estimation of technology-specific experience effects difficult. To test whether these phenomena mask the existence of technology-based experience effects, equation (3) was reestimated after dropping the scale interaction term η * INTERNET_i * $\text{lnASSETS}_{i,t}$. However, the results of these regressions were qualitatively similar to those reported in tables 5 and 6 for the full equation (3) specification.

Technology-based scale effects. There is somewhat stronger evidence of technology-based scale effects in the data, especially among the "survivor" Internet-only startups, which arguably are better-managed firms. The coefficient η on the term INTERNET_i * $\text{lnASSETS}_{i,t}$ is positive in all 10 ROA regressions and statistically significant in 5 of these regressions, including 3 of the 5 survivor bank regressions in table 6.[32] On average, a doubling of asset size is associated with a 148 basis point increase in ROA at survivor Internet-only startups, compared to only a 92 basis point increase at branching bank startups. This evidence is consistent with the hypothesis that banks using the Internet-only technology have access to deeper scale economies.

Note, however, that there is no similar evidence of technology-based scale effects in the ROE regressions; for example, the model 1 regressions in both tables 5 and 6 suggest that ROE remains flat as Internet-only banks grow larger. The link between ROA and ROE is the capital-to-asset ratio, and the EQUITY regressions confirm that this ratio declined significantly slower at the Internet-only banks than at the branching banks as banks grew their assets.[33] These results are consistent with the anecdotes reported in notes 6 and 7; based on this combined evidence, one might conclude that more stringent capital

31. The math for the first of these two calculations is LOANS = $.1122 \times \ln(2 \times \text{AGE}) = .1122 \times \ln 2 + .1122 \times \text{lnAGE} = .0777 + .1122 \times \text{lnAGE}$.

32. In addition, the estimated coefficient $\eta = .0073$ in the ROA random effects model 1 in table 6 is statistically different from zero at the 11% level of significance.

33. Several of the Internet-only banks went back to the market to raise substantial amounts of additional equity capital during their second year of operation.

regulation for Internet-only bank startups has suppressed returns to investors in those ventures.

The primary source of the technology-based scale gains in ROA appears to be cost scale economies. On average, total noninterest expenses (NIEXP) decline more quickly with asset size at the survivor Internet-only startups (−.0246 −.0152) than at the branching bank startups (−.0246). A similar, although more modest, result obtains for OTHEREXP. Both deposit rates and loan rates increase more quickly with asset size at the Internet-only startups (by an average of .0046 and .0052 basis points, respectively), but these two effects offset each other in SPREAD. As Internet-only startups grow larger, they also grow more slowly and generate relatively less output than comparable branching bank startups (GROWTH, DEPOSITS, LOANS).[34]

IX. Conclusions

As the Internet becomes more important for commerce, Internet Web sites become a more integral part of companies' business plans. One potential source of value in Internet-based business models comes from automation and increased scale: because automated processes typically require large fixed investments but reduce variable costs, e-commerce applications may substantially reduce per-unit costs or increase the optimal size of the firm. Another potential source of value in Internet-based business models comes from learning: because e-commerce applications are often (if not typically) introduced by startup firms, simply accumulating experience with a new business model can generate reductions in per-unit costs and increases in per-unit revenues over time.

This article introduces a framework for considering the implications of scale and learning at startup firms using nontraditional (e.g., Internet-based) business models. The framework allows learning to improve the performance of these firms in two ways: through general experience effects, which are available to all firms regardless of the business model they use, and technology-based experience effects, which are available only to firms that use the nontraditional business model. Similarly, the framework allows increased size to improve new firm performance in two ways: through general scale effects, which are available to all firms regardless of the business model they use, and technology-based scale effects, which are available only to firms that use the nontraditional business model. The banking industry, where startup firms are abundant and a number of these startups recently introduced a nontraditional and largely untried Internet-only business model, is a natural place to test for these differential learning and scale effects.

34. Reestimating eq. (3) without the experience interaction term η * INTERNET_i * $\ln\text{AGE}_{i,t}$ generated results that were qualitatively similar to those reported in tables 5 and 6.

An empirical analysis tests for the existence of these learning and scale effects for a dozen new Internet-only banks and thrifts that started up in the United States between 1997 and 2000, using 644 branching banks and thrifts that started up during the same time period as a performance benchmark. There is strong evidence of general experience effects available to all startups, but there is little evidence that technology-based learning accelerates the financial performance of Internet-only startups. On the other hand, there is evidence that increased scale yields a differentially greater improvement in financial performance for Internet-only startups relative to branching bank startups.[35] These results are robust across estimation techniques and stronger for banks with long-term commitments to the Internet-only business model, and they also tend to be associated with banks that exhibit strong cost control and conservative growth behaviors.

To date, most Internet-only banks and thrifts have struggled for profitability, and a substantial percentage of the firms that tried this business model abandoned it. As a result, the Internet-only model, once ballyhooed by banking pundits as the wave of the future, has lost favor and is generally not considered to be a viable business strategy for banking firms. To be sure, this study confirms the low average levels of profits at Internet-only banks, but it also reveals that some features of this business model have worked exactly as expected. For example, the typical Internet-only startup offered customers better prices (lower interest rates on loans and higher interest rates on deposits) than the average branching bank startup and grew substantially faster as well. However, reductions in overhead and other expenses have not materialized as expected, and this has acted as a drag on profits.

Against this ambiguous backdrop, the study identifies two phenomena that could improve the long-run odds for the Internet-only banking model. First, the evidence is consistent with the existence of technology-specific scale effects. As time passes and Internet-only banks grow larger, the resulting scale efficiencies may be large enough to close the remaining profitability gap with branching banks. This is an empirical question, and at this point in time, the potential size of any scale savings is unknown because most Internet-only banks are still relatively small. Second, the evidence is consistent with anecdotal reports that capital regulations have been administered more stringently with respect to Internet-only banks, suppressing the rate of return to investors in these ventures. As time passes and regulators gain experience and become more comfortable with this business model, these extranormal capital

35. These findings are consistent with at least one consulting firm study, which concluded that small size can be a deterrent to the successful application of Web-based banking technologies. See "Internet Banking Profit Seen Harder for Small Banks," *American Banker* (November 3, 2000): 10.

requirements could be relaxed, boosting returns and making the model more attractive to investors. This is a regulatory question, and it is difficult to know regulatory policy behavior will change until more is known about the risk profiles of Internet-only banks.

It is natural to wonder about the implications of these results for banks that use the click-and mortar business model, by far the dominant approach for Internet banking. Because click-and-mortar banks distribute some portion of their services over the Internet channel, they are likely to benefit from the existence of technology-based scale effects, as long as negative synergies from combining the branch and Web distribution channels are not large (e.g., migrating branch-based customers to the Internet may require banks to operate some of their branches at suboptimal scale). However, because click-and-mortar banks split their business volume between the branch channel and the Internet channel, they capture fewer technology-based scale economies than an Internet-only bank with similar business volume. There is little reliable data on how click-and-mortar banks split their business volume between these two channels, so the relative scale efficiencies achievable with these two different Internet banking strategies is unknown. As a (very crude) first approximation, to capture the same amount of technology-based scale savings as an Internet-only bank, one would expect that a click-and-mortar bank that runs 25% of its volume through its Web site would have to be four times as large as the Internet-only bank. Hence, click-and-mortar banks likely benefit from the scale gains associated with the Internet channel, but only to the extent that they can migrate their branch-based customers to their Web site. And this is easier said than done, because the value proposition that attracted branch-based retail customers to these banks in the first place (i.e., a convenient physical location and personalized service) can be easily destroyed if a bank pushes customers to migrate too quickly.

Although this study concludes that the Internet-only banking model is potentially viable under current conditions, this is no guarantee that Internet-only banks will continue to exist in the future; and if they do exist in the future, their market share is likely to be limited. Common sense and casual empiricism suggest that an increasing portion of future banking transactions will be conducted over the Internet, but they also suggest the majority of these transactions will occur at click-and-mortar banks. As the number of banks has declined in the United States, surviving banks have competed vigorously by offering customers increased choice and convenience, and the result has been an explosion in the number of branch offices and automated teller machines.[36]

36. DeYoung and Hunter (2003) provide evidence on the increasing number of bank branches, ATMs, and Internet Web sites between 1991 and 2000.

Click-and-mortar banking is a logical continuation of this progression. The share of the market captured by Internet-only banks ultimately depends on the number of retail customers that do not value these choices. Furthermore, the results generated here characterize the Internet-only banking model as a high-volume, low-cost strategy for delivering basic banking services, suggesting that Internet-only banks that serve this customer niche will be relatively large operations.

Appendix

Random Effects Models

The regression equations (1), (2), and (3) are estimated using both ordinary least squares estimation techniques and restricted maximum likelihood estimation techniques with random effects. The OLS approach pools the time-series/cross-section data, and assumes that the data are generated as follows:

$$y_{i,t} = \alpha + \beta' \mathbf{x}_{i,t} + \varepsilon_{i,t}, \tag{A1}$$

where i indexes banks, t indexes time, y is the dependent variable, α is a constant term to be estimated, $\mathbf{x}$ is a vector of exogenous variables, $\boldsymbol{\beta}$ is a vector of coefficients to be estimated, and ε is a random disturbance term with mean zero and variance σ^2 that is normally and independently distributed across all i and t. Thus, the OLS approach assumes that all observations $t = 1, T$ for bank i are independent of each other. In contrast, the random effects approaches assume that the data are generated as follows:

$$y_{i,t} = \alpha + \boldsymbol{\beta}' \mathbf{x}_{i,t} + u_i + \varepsilon_{i,t}, \tag{A2}$$

where u is a group-specific (bank-specific) disturbance term that enters the regression identically in each period for bank i. Because the true form of this bank-specific variation is unknown, four random effects models, identified as models 1 through 4 in the tables, are used in the regression analysis in tables 3 through 6.

Each of these models imposes a different structure on the variance-covariance matrix. Assuming the maximum number of $T = 10$ observations for each bank, random effects model 1 imposes the following "compound symmetry" structure on the 10-by-10 portion of the variance-covariance matrix corresponding to bank i:

$$\boldsymbol{\Omega}(\mathbf{1}) = \begin{bmatrix} \sigma^2 + \sigma_1 & \sigma_1 & \sigma_1 & \cdots & \sigma_1 \\ \sigma_1 & \sigma^2 + \sigma_1 & \sigma_1 & \cdots & \sigma_1 \\ \sigma_1 & \sigma_1 & \sigma^2 + \sigma_1 & \cdots & \sigma_1 \\ \vdots & \vdots & \vdots & \vdots & \\ \sigma_1 & \sigma_1 & \sigma_1 & \cdots & \sigma^2 + \sigma_1 \end{bmatrix}, \tag{A3}$$

TABLE A1 **Results for Equation (1) Using the Full Data Set, with ROA the Dependent Variable**

		Random Effects Model			
	OLS Regression	(1)	(2)	(3)	(4)
Intercept	−.1688***	−.2125***	−.2063***	−.2176***	−.1410***
	(.0054)	(.0087)	(.0092)	(.0097)	(.0080)
INB	−.0399***	−.0423***	−.0468***	−.0474***	−.0293***
	(.0028)	(.0054)	(.0051)	(.0056)	(.0043)
lnAGE	.0138***	.0121***	.0145***	.0144***	.0158***
	(.0006)	(.0008)	(.0008)	(.0008)	(.0009)
lnASSETS	.0112***	.0163***	.0152***	.0163***	.0088***
	(.0005)	(.0008)	(.0009)	(.0009)	(.0007)
QUARTER1	.0035***	.0052***	.0037***	.0041***	.0029***
	(.0009)	(.0008)	(.0007)	(.0007)	(.0006)
QUARTER2	.0030***	.0037***	.0028***	.0031***	.0022***
	(.0009)	(.0007)	(.0007)	(.0006)	(.0005)
QUARTER3	.0037***	.0039***	.0028***	.0032***	.0025***
	(.0009)	(.0007)	(.0005)	(.0005)	(.0004)
YEAR98	.0024	.0009	.0037**	.0038**	.0052***
	(.0018)	(.0015)	(.0017)	(.0016)	(.0019)
YEAR99	−.0007	−.0036**	.0025	.0020	.0041*
	(.0018)	(.0017)	(.0020)	(.0020)	(.0023)
YEAR00	.0006	−.0049**	.0024	.0012	.0035
	(.0018)	(.0021)	(.0023)	(.0024)	(.0026)
YEAR01	−.0015	−.0097***	−.0017	−.0035	−.0008
	(.0020)	(.0026)	(.0027)	(.0028)	(.0029)
ALLOWANCE	−1.4433***	−1.5164***	−2.2336***	−2.1514***	−1.7539***
	(.1152)	(.1427)	(.1623)	(.1588)	(.1261)
LOANS	.0337***	.0443***	.0344***	0357***	.0287***
	(.0021)	(.0027)	(.0029)	(.0029)	(.0025)
%REALESTATE	.0099***	.0015	.0066*	.0059	.0069**
	(.0024)	(.0036)	(.0038)	(.0039)	(.0035)
%BUSINESS	.0024	−.0076*	.0002	−.0014	.0031
	(.0029)	(.0039)	(.0042)	(.0042)	(.0039)
MBHC	.0034***	.0043***	.0058***	.0060***	.0028**
	(.0008)	(.0015)	(.0015)	(.0016)	(.0012)
THRIFT	−.0104***	−.0102***	−.0117***	−.0112***	−.0135***
	(.0012)	(.0024)	(.0023)	(.0025)	(.0019)
OCC	−.0021***	−.0024	−.0030*	−.0030*	−.0030**
	(.0008)	(.0016)	(.0015)	(.0017)	(.0012)
JOBGROWTH	.0929	−.0748	−.0217	−.0254	−.0292
	(.0772)	(.0704)	(.0582)	(.0603)	(.0483)
N	4742	4742	4742	4742	4742
Adjusted R^2	.4453				
Log likelihood		−24848	−25451	−25590	−26792

TABLE A2 Results for Equation (1) Using the Survivor Data Set, with ROA the Dependent Variable

		Random Effects Model			
	OLS Regression	(1)	(2)	(3)	(4)
Intercept	−.1695***	−.2128***	−.2071***	−.2175***	−.1337***
	(.0053)	(.0086)	(.0091)	(.0095)	(.0076)
INB	−.0238***	−.0289***	−.0303***	−.0319***	−.0139***
	(.0031)	(.0060)	(.0057)	(.0062)	(.0047)
lnAGE	.0140***	.0122***	.0147***	.0147***	.0155***
	(.0005)	(.0008)	(.0008)	(.0008)	(.0008)
lnASSETS	.0113***	.0162***	.0153***	.0163***	.0082***
	(.0005)	(.0008)	(.0009)	(.0009)	(.0007)
QUARTER1	.0033***	.0050***	.0035***	.0039***	.0025***
	(.0009)	(.0008)	(.0007)	(.0007)	(.0006)
QUARTER2	.0029***	.0037***	.0027***	.0029***	.0019***
	(.0009)	(.0007)	(.0006)	(.0006)	(.0005)
QUARTER3	.0038***	.0040***	.0030***	.0033***	.0025***
	(.0009)	(.0007)	(.0005)	(.0005)	(.0004)
YEAR98	.0023	.0008	.0039**	.0038**	.0054***
	(.0018)	(.0015)	(.0017)	(.0016)	(.0019)
YEAR99	−.0005	−.0036**	.0029	.0022	.0049**
	(.0017)	(.0017)	(.0020)	(.0020)	(.0023)
YEAR00	.0007	−.0050**	.0026	.0014	.0044*
	(.0017)	(.0021)	(.0023)	(.0023)	(.0026)
YEAR01	−.0013	−.0097***	−.0012	−.0031	.0007
	(.0020)	(.0025)	(.0027)	(.0028)	(0029)
ALLOWANCE	−1.4814***	−1.5435***	−2.2513***	−2.1837***	−1.7184***
	(.1129)	(.1405)	(.1590)	(.1559)	(.1206)
LOANS	.0327***	.0440***	.0333***	.0345***	.0279***
	(.0020)	(.0027)	(.0029)	(.0029)	(.0024)
%REALESTATE	.0091***	.0026	.0066*	.0064*	.0061*
	(.0024)	(.0035)	(.0038)	(.0038)	(.0034)
%BUSINESS	.0022	−.0063	.0005	−.0005	.0033
	(.0029)	(.0039)	(.0041)	(.0042)	(.0038)
MBHC	.0037***	.0046***	.0063***	.0064***	.0028**
	(.0008)	(.0015)	(.0015)	(.0016)	(.0011)
THRIFT	−.0097***	−.0099***	−.0112***	−.0108***	−.0128***
	(.0012)	(.0024)	(.0023)	(.0025)	(.0018)
OCC	−.0022***	−.0025	−.0032**	−.0031*	−.0030***
	(.0008)	(.0016)	(.0015)	(.0017)	(.0012)
JOBGROWTH	.0886	−.0776	−.0168	−.0265	−.0292
	(.0758)	(.0697)	(.0570)	(.0591)	(.0469)
N	4721	4721	4721	4721	4721
Adjusted R^2	.4482				
Log likelihood		−24892	−25561	−25691	−27002

TABLE A3 Results for Equation (2) Using the Full Data Set, with ROA the Dependent Variable

		Random Effects Model			
	OLS Regression	(1)	(2)	(3)	(4)
Intercept	−.1678***	−.2110***	−.2039***	−.2153***	−.1376***
	(.0054)	(.0087)	(.0091)	(.0096)	(.0078)
Internet bank 1	−.0037	v.0101	−.0077	−.0082	−.0038
	(.0118)	(.0179)	(.0191)	(.0198)	(.0204)
Internet bank 2	−.0327***	−.0348**	−.0407***	−.0422***	−.0215**
	(.0065)	(.0162)	(.0139)	(.0157)	(.0102)
Internet bank 3	−.0122*	−.0259	−.0235*	−.0294*	−.0177*
	(.0067)	(.0165)	(.0141)	(.0160)	(.0105)
Internet bank 4	−.1077***	−.1154***	−.1180***	−.1207***	−.1056***
	(.0067)	(.0164)	(.0141)	(.0159)	(.0103)
Internet bank 5	−.0073	−.0158	−.0096	−.0133	.0012
	(.0102)	(.0174)	(.0180)	(.0191)	(.0167)
Internet bank 6	−.0431***	−.0482***	−.0494***	−.0510**	−.0471**
	(.0118)	(.0179)	(.0191)	(.0199)	(.0204)
Internet bank 7	−.0543***	−.0512***	−.0596***	−.0573***	−.0405***
	(.0078)	(.0167)	(.0156)	(.0173)	(.0126)
Internet bank 8	−.0744***	−.0764***	−.0971***	−.0907***	−.1156***
	(.0102)	(.0173)	(.0179)	(.0190)	(.0166)
Internet bank 9	−.0289***	−.0313*	−.0362***	−.0407**	−.0076
	(.0066)	(.0164)	(.0140)	(.0158)	(.0103)
Internet bank 10	−.0390***	−.0446**	−.0448**	−.0444**	−.0313
	(.0118)	(.0178)	(.0190)	(.0198)	(.0203)
Internet bank 11	−.0139	−.0131	−.0167	−.0159	.0103
	(.0091)	(.0169)	(.0170)	(.0184)	(.0152)
Internet bank 12	−.0299***	−.0364**	−.0335**	−.0351**	−.0151
	(.0084)	(.0167)	(.0162)	(.0177)	(.0130)
lnAGE	.0141***	.0122***	.0147***	.0146***	.0156***
	(.0005)	(.0008)	(.0008)	(.0008)	(.0008)
lnASSETS	.0113***	.0162***	.0150***	.0162***	.0084***
	(.0005)	(.0008)	(.0009)	(.0009)	(.0007)
QUARTER1	.0034***	.0052***	.0036***	.0041***	.0027***
	(.0009)	(.0008)	(.0007)	(.0007)	(.0006)
QUARTER2	.0030***	.0037***	.0028***	.0030***	.0020***
	(.0009)	(.0007)	(.0006)	(.0006)	(.0005)
QUARTER3	.0037***	.0039***	.0028***	.0032***	.0024***
	(.0009)	(.0007)	(.0005)	(.0005)	(.0004)
YEAR98	.0024	.0009	.0038**	.0039**	.0057***
	(.0018)	(.0015)	(.0017)	(.0016)	(.0020)
YEAR99	−.0004	−.0034**	.0027	.0022	.0049**
	(.0017)	(.0017)	(.0020)	(.0020)	(.0024)
YEAR00	.0009	−.0047**	.0025	.0014	.0046*
	(.0017)	(.0021)	(.0023)	(.0024)	(.0026)
YEAR01	−.0013	−.0095***	−.0015	−.0032	.0007
	(.0020)	(.0025)	(.0027)	(.0028)	(.0029)
ALLOWANCE	−1.4877***	−1.5305***	−2.2353***	−2.1640***	−1.7392***
	(.1138)	(.1422)	(.1609)	(.1582)	(.1233)
LOANS	.0324***	.0436***	.0337***	.0350***	.0284***
	(.0021)	(.0027)	(.0029)	(.0029)	(.0025)
%REALESTATE	.0083***	.0012	.0059	.0054	.0075**
	(.0024)	(.0036)	(.0038)	(.0039)	(.0034)
%BUSINESS	.0011	−.0079**	−.0005	−.0019	.0041
	(.0029)	(.0039)	(.0042)	(.0042)	(.0039)

TABLE A3 **(*Continued*)**

	OLS Regression	Random Effects Model (1)	(2)	(3)	(4)
MBHC	.0037***	.0046***	.0062***	.0063***	.0030***
	(.0008)	(.0015)	(.0015)	(.0016)	(.0012)
THRIFT	−.0101***	−.0102***	−.0116***	−.0111***	−.0133***
	(.0012)	(.0025)	(.0023)	(.0025)	(.0019)
OCC	−.0023***	−.0027*	−.0033**	−.0033**	−.0034***
	(.0008)	(.0016)	(.0015)	(.0017)	(.0012)
JOBGROWTH	.0865	−.0713	−.0213	−.0234	−.0292
	(.0763)	(.0704)	(.0582)	(.0602)	(.0483)
N	4742	4742	4742	4742	4742
Adjusted R^2	.4643				
Log likelihood		−24816	−25433	−25563	−26792

which requires two disturbance parameters to be estimated. Random effects regression model (2) imposes the following "first-order autoregressive" structure on the portion of the variance-covariance matrix corresponding to bank i:

$$\mathbf{\Omega}(\mathbf{2}) = \begin{bmatrix} \sigma^2 & \sigma^2\rho & \sigma^2\rho^2 & \cdots & \sigma^2\rho^9 \\ \sigma^2\rho & \sigma^2 & \sigma^2\rho & \cdots & \sigma^2\rho^8 \\ \sigma^2\rho^2 & \sigma^2\rho & \sigma^2 & \cdots & \sigma^2\rho^7 \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \sigma^2\rho^9 & \sigma^2\rho^8 & \sigma^2\rho^7 & \cdots & \sigma^2 \end{bmatrix}, \tag{A4}$$

which also requires two disturbance parameters to be estimated. Random effects regression model (3) imposes the following "Toeplitz" structure on the portion of the variance-covariance matrix corresponding to bank i:

$$\mathbf{\Omega}(\mathbf{3}) = \begin{bmatrix} \sigma^2 & \sigma_1 & \sigma_2 & \cdots & \sigma_9 \\ \sigma_1 & \sigma^2 & \sigma_1 & \cdots & \sigma_8 \\ \sigma_2 & \sigma_1 & \sigma^2 & \cdots & \sigma_7 \\ \vdots & \vdots & \vdots & \cdots & \\ \sigma_9 & \sigma_8 & \sigma_7 & \cdots & \sigma^2 \end{bmatrix}, \tag{A5}$$

which requires 10 disturbance parameters to be estimated. Finally, random effects regression model (4) imposes an "unstructured" structure on the portion of the variance-covariance matrix corresponding to bank i:

$$\mathbf{\Omega}(\mathbf{4}) = \begin{bmatrix} \sigma_1^2 & \sigma_{21} & \sigma_{31} & \cdots & \sigma_{91} \\ \sigma_{21} & \sigma_2^2 & \sigma_{32} & \cdots & \sigma_{92} \\ \sigma_{31} & \sigma_{32} & \sigma_3^2 & \cdots & \sigma_{93} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \sigma_{91} & \sigma_{92} & \sigma_{93} & \cdots & \sigma_{10}^2 \end{bmatrix}, \tag{A6}$$

TABLE A4 Results for Equation (3) Using the Full Data Set, with ROA the Dependent Variable

		Random Effects Model			
	OLS Regression	(1)	(2)	(3)	(4)
Intercept	−.1682***	−.2100***	−.2039***	−.2146***	−.1393***
	(.0055)	(.0090)	(.0094)	(.0099)	(.0081)
INB	−.0664**	−.1103**	−.1344**	−.1430***	−.0891*
	(0310)	(.0443)	(.0540)	(.0547)	(.0505)
lnAGE	.0139***	.0122***	.0147***	.0146***	.0159***
	(.0006)	(.0008)	(.0008)	(.0008)	(.0009)
lnAGE * INB	−.0040	−.0062	−.0080	−.0079	−.0007
	(.0040)	(.0046)	(.0054)	(.0053)	(.0059)
lnASSETS	.0111***	.0160***	.0150***	.0160***	.0087***
	(.0005)	(.0009)	(.0009)	(.0009)	(.0007)
lnASSETS * INB	.0027	.0064	.0082*	.0089*	.0050
	(.0028)	(.0041)	(.0049)	(.0050)	(.0046)
QUARTER1	.0035***	.0052***	.0037***	.0041***	.0029***
	(.0009)	(.0008)	(.0007)	(.0007)	(.0006)
QUARTER2	.0030***	.0037***	.0028***	.0031***	.0022***
	(.0009)	(.0007)	(.0007)	(.0006)	(.0005)
QUARTER3	.0037***	.0039***	.0028***	.0032***	.0025***
	(.0009)	(.0007)	(.0005)	(.0005)	(.0004)
YEAR98	.0024	.0009	.0037**	.0038**	.0052***
	(.0018)	(.0015)	(.0017)	(.0016)	(.0019)
YEAR99	−.0007	−.0036**	.0025	.0019	.0042*
	(.0018)	(.0017)	(.0020)	(.0020)	(.0023)
YEAR00	.0006	−.0050**	.0023	.0011	.0036
	(.0018)	(.0021)	(.0023)	(.0024)	(.0026)
YEAR01	−.0016	−.0098***	−.0017	−.0036	−.0007
	(.0020)	(.0026)	(.0027)	(.0028)	(0029)
ALLOWANCE	−1.4469***	−1.5172***	−2.2422***	−2.1592***	−1.7520***
	(.1153)	(.1430)	(.1624)	(.1589)	(.1263)
LOANS	.0338***	.0443***	.0345***	.0358***	.0286***
	(.0021)	(.0027)	(.0029)	(.0029)	(.0025)
%REALESTATE	.0099***	.0015	.0065*	.0058	.0067*
	(.0024)	(.0036)	(.0038)	(.0039)	(.0035)
%BUSINESS	.0025	−.0076*	.0001	−.0015	.0028
	(.0029)	(.0039)	(.0042)	(.0042)	(.0039)
MBHC	.0034***	.0043***	.0058***	.0059***	.0027**
	(.0008)	(.0015)	(.0015)	(.0016)	(.0012)
THRIFT	−.0104***	−.0103***	−.0118***	−.0114***	−.0136***
	(.0012)	(.0024)	(.0023)	(.0025)	(.0019)
OCC	−.0021***	−.0024	−.0030*	−.0030*	−.0030**
	(.0008)	(.0016)	(.0015)	(.0017)	(.0012)
JOBGROWTH	.0914	−.0802	−.0249	−.0296	−.0286
	(.0773)	(.0709)	(.0583)	(.0605)	(.0484)
N	4742	4742	4742	4742	4742
Adjusted R^2	.4452				
Log likelihood		−24832	−25436	−25576	−26776

TABLE A5 Results for Equation (3) Using the Survivor Data Set, with ROA the Dependent Variable

	OLS Regression	Random Effects Model (1)	(2)	(3)	(4)
Intercept	−.1676***	−.2102***	−.2040***	−.2139***	−.1337***
	(.0054)	(.0088)	(.0092)	(.0096)	(.0077)
INB	−.1016***	−.0655	−.1346**	−.1422**	−.0025
	(.0339)	(.0485)	(.0579)	(.0584)	(.0542)
lnAGE	.0140***	.0123***	.0148***	.0148***	.0154***
	(.0005)	(.0008)	(.0008)	(.0008)	(.0008)
lnAGE * INB	.0004	.0014	−.0023	−0.0022	.0062
	(.0045)	(.0055)	(.0061)	(.0059)	(.0068)
lnASSETS	.0112***	.0160***	.0150***	.0159***	.0082***
	(.0005)	(.0008)	(.0009)	(.0009)	(.0007)
lnASSETS * INB	.0065**	.0030	.0091*	.0096*	−.0018
	(.0031)	(.0045)	(.0052)	(.0053)	(.0049)
QUARTER1	.0033***	.0050***	.0035***	.0039***	.0025***
	(.0009)	(.0008)	(.0007)	(.0007)	(.0006)
QUARTER2	.0029***	.0037***	.0027***	.0029***	.0019***
	(.0009)	(.0007)	(.0006)	(.0006)	(.0005)
QUARTER3	.0038***	.0040***	.0030***	.0033***	.0025***
	(.0009)	(.0007)	(.0005)	(.0005)	(.0004)
YEAR98	.0024	.0009	.0039**	.0039**	.0054***
	(.0018)	(.0015)	(.0017)	(.0016)	(.0019)
YEAR99	−.0004	−.0035**	.0029	.0022	.0049**
	(.0017)	(.0017)	(.0020)	(.0020)	(.0023)
YEAR00	.0008	−.0049**	.0026	.0014	.0045*
	(.0017)	(.0021)	(.0023)	(.0023)	(.0026)
YEAR01	−.0012	−.0095***	−.0012	−.0030	.0008
	(.0020)	(.0025)	(.0027)	(.0028)	(.0029)
ALLOWANCE	−1.4813***	−1.5312***	−2.2534***	−2.1855***	−1.7139***
	(.1128)	(.1407)	(.1590)	(.1558)	(.1207)
LOANS	.0328***	.0439***	.0334***	.0346***	.0278***
	(.0020)	(.0027)	(.0029)	(.0029)	(.0024)
%REALESTATE	.0089***	.0025	.0063*	.0062	.0061*
	(.0024)	(.0035)	(.0038)	(.0038)	(.0034)
%BUSINESS	.0019	−.0065*	.0001	−.0008	.0033
	(.0029)	(.0039)	(.0041)	(.0042)	(.0038)
MBHC	.0037***	.0046***	.0063***	.0063***	.0028**
	(.0008)	(.0015)	(.0015)	(.0016)	(.0011)
THRIFT	−.0097***	−.0099***	−.0113***	−.0109***	−.0127***
	(.0012)	(.0024)	(.0023)	(.0025)	(.0018)
OCC	−.0022***	−.0025	−.0031**	−.0031*	−.0030***
	(.0008)	(.0016)	(.0015)	(.0017)	(.0012)
JOBGROWTH	.0941	−.0704	−.0154	−.0243	−.0273
	(.0758)	(.0700)	(.0571)	(.0592)	(.0469)
N	4721	4721	4721	4721	4721
Adjusted R^2	.4488				
Log likelihood		−24875	−25547	−25678	−26986

which requires 45 disturbance parameters to be estimated. Regardless of random effects structure, the full variance-covariance matrix has the following block diagonal structure:

$$\mathbf{VC} = \begin{bmatrix} \boldsymbol{\Omega} & 0 & 0 & \cdots & 0 \\ 0 & \boldsymbol{\Omega} & 0 & \cdots & 0 \\ 0 & 0 & \boldsymbol{\Omega} & \cdots & 0 \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & 0 & \cdots & \boldsymbol{\Omega} \end{bmatrix}. \tag{A7}$$

A more-detailed presentation of these four variance-covariance structures can be found in the *SAS/STAT user's guide, version 8* (Cary, NC: SAS Institute, 1999), pp. 2133–45. A more-complete discussion of random effects models can be found in Greene (1997), pp, 623–35.

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