Is the Traditional Banking Model a Survivor?

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Abstract: We test whether small US commercial banks that use a traditional business model are more likely to survive than non-traditional banks during both good and bad economic climates. Our concept of bank survival is derived from Stigler (1958) and includes any bank that does not fail or is not acquired. We define traditional banking by four hallmark characteristics: Relationship loans, core deposit funding, revenue streams from traditional banking services, and physical bank branches. Banks that adhered more closely to this business strategy were an estimated 8 to 13 percentage points more likely to survive from 1997 through 2012 compared to other small banks using less traditional business strategies. This survival advantage approximately doubled during the financial crisis period.

Keywords: bank business model; financial crisis; survivorship
JEL classification: G21; G01

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1. Introduction

The global financial crisis of 2007-2009 resulted in severe financial distress, insolvency, and in some cases government bailout, for thousands of banking companies in Europe and the US. As they looked back at this episode, researchers focused nearly exclusively on the question "What went wrong?" Their conclusions—on the causes of bank insolvency, illiquidity, and systemic risk—have helped shape reforms in bank regulation aimed at reducing the likelihood of similar episodes in the future. This is a logical and well-worn approach, and it mirrors the ways that researchers and policymakers have proceeded in the wake of previous banking crises. But this is also an incomplete approach. Rather than focusing only on "What went wrong?" and then prescribing policies that attempt to prevent banks from repeating those mistakes, why not also attempt to identify "What went right?" and then encourage banks to embrace those positive practices?

Of the 521 US banks that failed or required government financial assistance from January 2008 through April 2015, 502 were so-called 'community banks' with assets less than $10 billion.[1] Thus, the aftermath of the financial crisis supports the conventional narrative that small commercial banking companies are dinosaurs destined for extinction from banking markets. Indeed, between 1984 and 2007, the number of community banks in the US declined by roughly half, the result of bank failures, bank mergers and acquisitions, and bank holding company reorganizations. But approximately six thousand community banking organizations continued to operate in the US after the crisis (FDIC 2012), approximately twelve times the number of community banks that disappeared. What went right for these surviving banks?

In this study, we focus on the business models used by US community banks, carefully differentiating banks that exhibit 'traditional' banking characteristics from banks that do not. We then test whether community banks that used a more traditional banking approach—that is, banks that relied primarily on relationship lending, core deposit funding, balance sheet and other traditional sources of

[1] Data from the Federal Deposit Insurance Corporation website (www.FDIC.gov) at the time of the first draft of this paper. The reported result is based on the broad definition of a community bank that we use in this study, which includes banks with less than $10 billion in assets. Based on a more conservative asset size threshold of $2 billion, 477 of the 521 failed banks were community banks.

revenue, and physical branch distribution—have been more or less likely to survive than other community banks, both through good economic times and bad economic times.

Our investigation is in the spirit of Stigler's (1958) survivorship concept, in which a researcher allows the competitive marketplace to naturally and endogenously reveal successful and unsuccessful business practices. The approach is simple and straightforward: A bank is identified as a 'survivor' if it is still operating at the end of some measured period of time, while a bank that exits the market during that same time period is a 'non-survivor.' The survivorship concept makes no distinctions among the various avenues that a bank might use to exit the market; any avenue of exit indicates that the bank either did not or could not survive on its own. A financial failure (i.e., a bank that disappears due to insolvency or illiquidity) is treated no differently than a strategic failure (i.e., a bank that disappears as the target in a merger, acquisition or holding company reorganization).

We apply this survivorship concept to US commercial banking companies starting in 1997. This comes immediately after the full implementation of the Riegle-Neal Act (1994) which allowed nationwide bank competition, thus ensuring that all of the banks in our data faced the potential competitive pressure necessary for the Stiglerian survivorship concept to work.[2] We then observe which of these banks survived through 2012. Finally, we test whether the surviving banks were more or less likely than the non-survivors to have been using traditional banking business models. We define a bank as 'traditional' if it has above average values for at least three of the following four variables relative to similarly sized banks: Relationship loans-to-assets; core deposits-to-assets; branches-to-assets; and the percentage of its operating revenues generated from traditional banking products and services.

We focus our investigation on banks with between \$500 million and \$10 billion of assets (2006 dollars). Previous research suggests that banks smaller than \$500 million face a competitive disadvantage regardless of their business model; they are too small to survive in truly competitive

[2] While Riegle-Neal was signed in 1994, states did not have to come into full compliance until 1996. While many states had allowed some form of out-of-state competition prior to 1996, Riegle-Neal increased competitive pressure on banks in all states by making entry possible in any state from any state. Evidence provided by DeYoung, Hasan and Kirchhoff (1998) and Evanoff and Örs (2008) is strongly consistent with idea that geographic bank deregulation is associated with an increase in competitive pressure.

markets because they leave a substantial portion of available scale economies unexploited (DeYoung 2013). The data for sub-$500 million banks in Figure 1 strongly reinforce this notion. At the other extreme, researchers and regulators have for several decades simply used $1 billion of assets as a convenient upper bound for defining community banks; however, we are unaware of any research on the diseconomies of scale associated with the traditional banking model. We expand this upper bound to $10 billion to account for the possibility that technological advances (e.g., cell phones, the Internet) have over time enhanced banks' abilities to maintain traditional in-person relationships with depositors and borrowers at longer distances (Berger and DeYoung 2006).[3]

Our results indicate that the traditional banking business model, as we define it here, is associated with an increased probability of bank survival. Simple univariate analysis indicates that traditional banks were on average 19 percent more likely than non-traditional banks to survive from 1997 through 2012. A more sophisticated statistical analysis (pooled and panel data models, year and random effects, correction for selection bias) indicates that the average traditional bank was 8 to 13 percentage points more likely to survive from 1997 through 2012 than the average nontraditional bank. Perhaps most importantly, we show that the survival advantage of traditional banks relative to nontraditional banks grew stronger during the financial crisis, when bank balance sheets came under substantial stress.

Our findings suggest that banking industry consolidation, both in the US and elsewhere, may stop short of the complete extinction of community banks. Under normal economic conditions, the traditional banking business model appears to be financially and strategically viable, so long as the model is applied to a bank of adequate scale, is accompanied by effective management, and is not overburdened with fixed regulatory costs that impose an artificial size disadvantage on small banks. Moreover, under stressful economic conditions, small banks that adhere to traditional banking practices appear to be more stable than their rivals. Because banking technologies and competitive business strategies migrate easily across national borders, and the regulatory practices of different countries have

[3] Banks with assets in excess of $10 billion eventually gain access to high-volume, repetitive-use production processes—such as credit-scored lending, asset securitization, and online payments services—that drive down their per unit costs dramatically. The traditional in-person relationship banking approach is antithetical to banks that are large enough to fully exploit these high-volume production processes.

been converging over time, our findings regarding the survivability of the traditional banking model in the US should also hold, at least in part, for small banks in other countries. Of course, our findings are conditional on the information, communications, and regulatory technologies present during our 1997-2012 sample period; changes in these underlying conditions could undermine the competitive advantages of the traditional banking model that we find here.

The remainder of the paper is organized as follows. In section 2 we review the previous studies that are most relevant for our analysis. In section 3 we describe data set and consider the general strengths and potential weaknesses of our unique methodological approach. In section 4 we examine the strategic and financial attributes of these banks, and explore which of these attributes were most closely related to banks' surviving our 1997-2012 sample period. In section 5 we separate our data into traditional banks and nontraditional banks, and perform simple survivorship tests in the spirit of Stigler (1958). In sections 6 through 8 we extend our analysis to include more sophisticated multivariate econometric models. Section 9 summarizes and concludes.

2. Literature Review

The central concept in this study is bank survival. We define this concept simply, as whether a bank that is operating at the beginning of some pre-determined time period is still operating at the end of that time period. Moreover, in our analysis the manner in which a non-surviving bank disappears is immaterial; we treat exit via insolvency (financial failure) and exit via acquisition (strategic failure) identically. Non-surviving banks will not be around to provide financial services next year regardless of how they passed away, but surviving banks will. For this reason, we are keenly interested in what makes banks survive.

This perspective is unique in the banking literature. Two largely separate strands of the literature focus squarely on bank exit. There is a large body of research on bank financial failure, most of which seeks to identify the determinants of banks insolvency. This research has been driven chiefly by the needs of bank supervisors and regulators to understand whether and how banking crises can spill over into the macro-economy. There is also a large body of research on what we refer to here as bank strategic failure, in which banks are targeted and taken over by other banks. While this research has been driven chiefly by the interests of academic finance researchers, it has intrinsic value for capital gains-seeking investors looking to identify banks likely to become acquisition targets. Only a small handful of studies jointly examine both financial failure and strategic failure.[4]

From a microeconomic perspective, survival is a signal that the strategic decisions the bank made in the past were largely correct decisions. From a macroeconomic perspective, the population of banks that survives has, by definition, been providing the financial services demanded by a diverse population of bank customers. To the extent that the traditional community banking model is prominent within these survivors, then small and informationally opaque businesses—i.e., firms that create large amounts of new jobs in the macro-economy—will receive the relationship finance support that they need (Berger, Miller, Petersen, Rajan, and Stein, 2005; Chakraborty and Hu, 2006).

The brief review of the bank exit literature that follows is not meant to be all inclusive. We want to illustrate that the bank exit literature is bifurcated into a financial failure subgroup and a strategic failure subgroup. And we want to identify the determinants of bank exit that overlap in these two sets of studies, as these may be instructive for determining the causes of bank survival.

2.1. Exit by financial failure

The first bank failure studies documented the wave of US bank and thrift failures in late 1980s and early 1990s. These studies were characterized as 'early-warning' models for preemptively detecting potential financial distress, thus allowing bank supervisors to attempt corrective actions. This set of studies includes, among many others, Thomson (1991), Whalen (1991), Cole and Gunther (1995), Wheelock and Wilson (2000), DeYoung (2003b), Oshinsky and Olin (2006) and Schaeck (2008). This body of research collectively identified a standard set of variables useful for predicting bank financial distress and failure, including rapid loan growth, overreliance on loans backed by commercial real estate, and heavy use of wholesale funding and interbank funding sources.

A second and more recent set of studies examine the determinants of US commercial bank failures, predominantly during the 2007-2009 financial crisis. A subset of three studies focus on banking activities. Cole and White (2012) found that the primary drivers of crisis-era bank failures

[4] One such example is DeYoung (2003a).

were strikingly similar to the primary drivers of bank failures during the 1980s and 1990s, namely, high concentrations of commercial real estate and construction loans. Antoniades (2015) showed that increased investment in private-label (typically riskier) MBS prior to the crisis significantly increased the chances of bank failure during the crisis, but increased investment in agency (typically safer) MBS had no similar effect. DeYoung and Torna (2013) found that income from fee-for-service activities (e.g., mortgage servicing, securities brokerage, insurance sales and other activities that do not require banks to hold risky assets) helped prevent financially distressed banks from failing, while stakeholder activities (investment banking, venture capital, proprietary trading or other activities that often do require banks to hold risky assets) helped banks avoid financial distress but accelerated failure for banks that did become distressed.

Other studies of US bank failures during the financial crisis look at the role of bank capital, bank liquidity, economic conditions, and corporate governance. Ng and Roychowdhury (2014) find that loan loss allowances included in Tier 2 regulatory capital (add-backs) increased the risk of bank failure during the period 2007-2010. Hong, Huang, and Wu (2014) investigate whether a bank's liquidity position affects its risk of failure, and find that failure is negatively correlated with the (not-yet-implemented) Basel III Net Stable Funding Ratio, but is positively correlated with the (not-yet-implemented) Basel III Liquidity Coverage Ratio. Consistent with previous bank failure episodes, Aubuchon and Wheelock (2010) find that bank failure rates between 2007 and 2010 were higher in states that suffered the strongest economic downturns and the highest rates of distress in real estate markets. Berger, Imbierowicz and Rauch (2016) investigate the impact of bank ownership structure and find that failure risk increases at banks in which lower-level managers (e.g., vice-presidents) have larger shareholdings.

2.2. Exit by strategic failure

When a bank wishes to grow, it has two choices: It can expand internally which tends to be a slow and gradual process, or it can expand via acquisition which holds the promise of fast and immediate results. Unlike internal expansion, in which a bank grows by scaling up its existing business model (i.e., its mix of inputs, outputs, and managerial practices), expansion via acquisition grafts an outside business model onto an existing bank. To avoid post-acquisition frictions, it follows that an acquisitive bank will take great care when evaluating the characteristics of its potential target banks.

Researchers have identified a number of desirable and undesirable target bank characteristics. Wheelock and Wilson (2004) and Akhigbe, Madura and Whyte (2004) found that the chances of a US bank being acquired is higher if the target bank is relatively less profitable than the acquiring bank. An earlier study by Wheelock and Wilson (2000) found that banks with lower capital ratios are more likely to be acquisition targets. These studies suggest the existence of an efficient market for corporate control in which well-run banks purchase poorly run banks and put the acquired resources to more productive uses. Studies of European bank mergers have found similar results. Beitel, Schiereck and Wahrenburg (2004) and Pasiouras, Tanna and Zopounidis (2007) showed that targets are less cost- or profit-efficient than acquirers on average. Focarelli, Panetta and Salleo (2002) found that targets in Italian bank acquisitions have relatively poor credit management, and that bank M&As tend to result in improved credit allocation and loan portfolio quality.

There are also some counter-results. Valkanov and Kleimeier (2007) examined large bank deals in the US and Europe between 1997 and 2003; they found little difference in the capital strength of European banks engaged in M&A activity, and they found that US target banks tended to be more highly capitalized than their acquirers. In a study of distressed and non-distressed German bank mergers, Koetter, et al. (2007) found relatively poor financial performance at highly acquisitive banks. Hosono, Sakai and Tsuru (2006) studied bank mergers in Japan, and found that cost- and profit-inefficient banks were the banks most likely to engage in M&A activity.

2.3. Bank success during the financial crisis.

We are unaware of any study that tests explicitly whether banks that practice a traditional banking business model have been more or less likely to survive over time.[5] However, two studies have focused on US banks that performed especially well during the financial crisis, and attempted to isolate the determining factors of this good performance. Brastow, et al. (2012) conducted in-depth interviews

[5] Tangential to our objective in this paper, Berger and Bouwman (2013) studied the impact of bank capital on small bank survival between 1984 and 2010, and found that holding high stores of financial capital helped small banks survive during all portions of the business cycle. In contrast, high capital levels helped larger banks survive mainly during banking crises.

with nine small US banks in the Fifth Federal Reserve District that maintained high supervisory safety and soundness ratings from 2000 through 2011. The interviews revealed, among other things, a commitment to "conservative business models" based on relationship banking, careful loan underwriting, and slow growth. In addition, the authors compared these nine healthy banks to eight Fifth District banks of similar sizes that lost their high supervisory ratings during the financial crisis. The healthy banks were more reliant on core deposit funding, had less concentrated (i.e., more diversified) loan portfolios, and made fewer commercial real estate loans. Gilbert, Meyer and Fuchs (2013) used a similar research method, but focused on a much larger sample of 702 "thriving" US community banks that maintained the very highest supervisory rating every year from 2006 through 2011. They compared these thriving banks to 4,525 community banks that operated from 2006 through 2011 with lower supervisory ratings, and found results largely consistent with the earlier study by Brastow, et al. (2012). On average, the thriving banks exhibited slower asset growth, were more reliant on core deposit funding, made fewer commercial real estate loans, and maintained greater asset liquidity (lower loan-to-assets ratios). Based on follow-up telephone interviews with 28 of the thriving banks, the authors were unable to find any overarching consistency across the business strategies of these banks.

3. Data

For the purpose of this study, a 'banking company' is either a commercial bank holding company (containing one or more commercial banks) or a free-standing commercial bank not organized as a holding company. We collect financial statement data for multiple-bank holding companies from the Federal Reserve Y-9C consolidated bank holding company database. We collect financial statement data for single-bank holding companies and free-standing banks from the Reports of Condition and Income (call report) database. We collect data on the geographic locations of bank branches and deposits from the FDIC's Summary of Deposits database. Data on bank failures and bank acquisitions comes from FDIC and National Information Center websites. For the remainder of this study, we use the terms 'bank' and 'banking company' interchangeably.

Table 1 outlines the construction of our data set. At year-end 1997 there were 9,050 commercial banking companies—1,577 multiple-bank holding companies, 4,488 single-bank holding companies, and 2,985 free-standing banks—operating in the United States. Using standard filters, we remove 2,162 banking companies with substantial foreign ownership shares, with incomplete financial information, with unusually low levels of loans or deposits, banks that were only recently chartered, and second-tier holding companies.[6] Of the 6,888 banks that remain in the data after filtering, a total of 2,724 banks exited the industry during our 1997-2012 data period, leaving 4,164 banks still operating at year-end 2012. The non-survivors included 2,341 acquisition targets, 281 insolvencies that were seized by the FDIC;[7] 73 banks that were voluntarily closed or liquidated by their owners; 3 banks that would have failed had they not received Troubled Asset Relief Program (TARP) capital injections,[8] and 26 banks whose reason for exiting was not disclosed.

3.1. Viable bank size

When deregulation exposed US commercial banks to increased competition in the 1980s and 1990s, inefficient banks that were previously shielded from competition began to exit from the industry. The US banking system at that time contained over ten thousand very small banks, and most of the exiting banks were those that had been operating at suboptimal scale. As shown in Figure 1, the population of banks with assets less than $500 million declined radically during our 1997-2012 sample period. The population of banks with $300 to $500 million in assets declined by approximately 10%, banks with $100 to $300 million in assets declined by 28%, and banks smaller than this declined by a staggering 59%. Econometric estimates of bank scale economies predicted this pattern of exit. For

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[6] We filtered out 591 banks with foreign ownership greater than 50%; an additional 927 banks that did not report complete balance sheet data; an additional 63 banks that invested less than 10% of their assets in loans to households and businesses; an additional 27 banks that used deposits to fund less than 2% of their assets; an additional 398 banks that were less than 5 years old; and an additional 156 bank holding companies that were themselves already accounted for as subsidiaries of other bank holding companies.

[7] The FDIC has a variety of resolution methods for the failed banks that it seizes. Of the 281 banks that failed during 1997-2012, the FDIC arranged 183 acquisitions by other banks along with financial assistance, arranged 91 acquisitions by other banks without financial assistance, and liquidated the assets of 7 failed banks.

[8] We tracked all 263 of the banks in our sample that received a TARP capital injection, beginning in the quarter t in which their received the equity injection. If the private equity position of these banks (i.e., total equity capital minus the amount injected by the government) became negative in any future quarter t+s, then we assumed that the bank would have failed but for the government assistance.

example, McAllister and McManus (1993) and Wheelock and Wilson (2001) found substantial increasing returns to scale for banks with assets less than $500 million.[9]

In contrast, banks with assets between $500 million and $2 billion increased by about 21%, while banks between $2 and $10 billion increased by 14%, during the same time period; this during a time period when the total population of US banking companies was declining by about one-third. The Stiglerian interpretation of these data is that banks smaller than $500 million faced a competitive disadvantage because they were scale-inefficient. (Note that while scale inefficiency is the culprit in this case, a correct interpretation of the Stiglerian message is that market competition will eliminate firms with inefficiencies of all types, including technical inefficiency, allocative inefficiency, and scale inefficiency.) Insufficient size reduced the ability of these banks to earn a competitive return or to survive external shocks—not because the traditional banking model that most of these banks were using was non-viable business strategy, *but because these banks were simply too small to successfully implement any standard banking business model in a competitive banking market*. Thus, using these banks to test the viability of any banking business model would bias against finding viability. For this reason we exclude banks with assets less than $500 million from our main tests.

Note that as the number of banks between $500 million and $10 billion increased, the number of banks with assets over $10 billion actually decreased. Both of these phenomena are indicative of strategic choices. The former implies that small banks grew across the $500 million threshold (largely via acquiring other small banks) in order to capture the scale economies available in the traditional banking business model, but stayed small enough to effectively implement the traditional banking model. In-person relationships with retail and small business customers become more difficult to initiate and maintain as a bank grows larger and more organizationally complex. For this reason, we exclude banks with assets greater than $10 billion from our sample.[10] The latter reflects industry

[9] More recent studies of bank scale economies have tended to focus on large banks, and do not produce a consensus. Wheelock and Wilson (2012) and Hughes and Mester (2013) find potential scale economies at the very largest banking companies, but Davies and Tracy (2014) find constant returns to scale for these banks. For two different approaches to thinking about scale economies at banks, see DeYoung (2010, 2013) and Hughes and Mester (2015).

[10] While there is no previous research on the size at which a bank becomes too large to be a successful traditional bank, $1 billion has long been used as a convenient upper bound to define a "community banks." To account for inflation, we double this crude threshold to $2 billion. (The US Consumer Price Index approximately doubled

consolidation from repeated mega-mergers among large and very large banks. These mergers were aimed primarily at gaining the large scale necessary to optimize new information and financial technologies (e.g., online services, automated loan origination, asset securitization) central to a non-traditional transactions banking business model in which banks can profitably abandon relationship banking in favor of a high volume, repetitive transactions approach that sharply drives down per unit costs (DeYoung 2013, 2015).[11]

Our main sample includes 546 banking companies with assets between $500 million and $10 billion (2006 dollars) at year-end 1997. Within this group, we test whether banks using a traditional banking business model were more likely to survive through year-end 2012. Table 1 displays the eventual outcomes for these banks. Among these 546 banks, 244 survived to the end of our sample period while 302 banks did not survive. Of the non-surviving banks, 252 banks exited via acquisition, 34 banks either failed or closed voluntarily, and 16 exited for reasons that were not disclosed.[12] Importantly, across the entire sample period, the mean annual ROA for the 252 acquired banks (0.28%) was 60 basis points lower on average than the mean annual ROA for the 244 surviving banks (0.88%). This is consistent with our Stiglerian contention that exit via acquisition (for this size class of banks) is on average consistent with strategic failure, and is certainly not consistent with strategic success.

3.2. Strategic failure

The largest portion of the non-surviving banks were healthy banks that disappeared as acquisition targets. The bank M&A market was highly active during our 1997-2012 sample period, with more than 300 healthy US commercial banks acquired annually on average.[13] In our Stiglerian framework, we describe these banks as strategic failures—that is, the business models, management

from 115.4 at year-end 1987 to 229.6 at the end of our 1997-2012 sample period.) We retain banks as large as $10 million in our sample to allow for the possibility that information and communications innovations during our sample period made it possible for somewhat larger banks to maintain in-person banking relationships (Berger and DeYoung 2006).

[11] See DeYoung (2013, 2015) for a detailed description of the transactions banking model. For the very largest banking companies, growing larger was also aimed at accessing the implicit and explicit subsidies associated with too-big-to-fail status.

[12] These 16 banks are excluded from our regression tests.

[13] Data from the Federal Deposit Insurance Corporation website.

teams, geographic locations, or other characteristics of these acquired banks made them less valuable on their own than as part of the banks that acquired them.

Categorizing acquired banks as strategic failures presumes a reasonably efficient market for corporate control. In an efficient market, strategically failing banks are likely to receive bids in excess of their ongoing franchise values (new owners can redeploy these banks' resources more efficiently) and as such the owners of these banks have an incentive to sell. In contrast, strategically successful banks are less likely to receive bids in excess of their ongoing franchise values (new owners will have difficulty adding value to already successful banks) and as such these banks are unlikely to change hands. Moreover, regardless of whether a bank is strategically successful or strategically unsuccessful, its franchise value tends to *decrease* after it is acquired, due largely to an exodus of local depositors unhappy with changes being made by new ownership.[14] This is a well-known phenomenon and in an efficient market potential acquirers will adjust their offer prices downward to account for it, resulting in a price wedge that further reduces the chances that a strategically successful community bank will be acquired. Note that this price wedge will be larger for targeted banks that use the traditional business model, because the franchise values of these banks reflect disproportionate investment in bank employees for the purpose of creating and maintaining in-person customer relationships—investments that will deteriorate in a post-merger scenario as depositor flight reduces the value of these employees.

While we are unaware of any research that empirically documents this economic logic, we find evidence consistent with it for the subsample of banks in our data that were acquired. For acquired banks using a more traditional business model (i.e., *Traditional Index* above the subsample median), we find an average 8.8% reduction in gross bank employment after the merger, but only a 0.6% reduction for the remainder of the acquired banks using less traditional business models.[15] In our

[14] Industry analysts have found that depositor attrition rates increase by three-quarters or more, on average at banks in the months after they are acquired (J.D. Power 2009, Deloitte 2010, Gallop 2015). Indeed, Keeton (2000) and Berger, et al (2004) both found that new banks are more likely to start up in markets where small banks have been acquired, chiefly because key banking inputs like deposit funding, loan officers, and local business borrowers become available in those places post-merger.

[15] Gross bank employment is the combined employment at the acquiring and target banks. We calculate the percentage change in this measure from one quarter before to eight quarters after the mergers. We perform this calculation for the 50 (out of 252) mergers in which the acquiring bank made no other acquisitions within the two-year window, and then calculate averages for the 25 mergers in which the target banks was above (or below) the median in terms of *Traditional Index*. The difference between 8.8% and 0.6% is statistically significant.

methodological parlance, the former are strategically failed traditional banks and the latter are strategically failed non-traditional banks. While this is crude evidence to be sure, it is nonetheless consistent with our maintained assumption regarding strategic failures: In an efficient market for corporate control, we are less likely to observe acquisitions of successful soft information-based relationship banks (they only receive offers below their ongoing stand-alone values) than acquisitions of either unsuccessful soft information-based relationship banks or successful hard information-based banks.

4. Univariate survival analysis

Our analysis begins with simple univariate comparisons of the 244 surviving and 302 non-surviving banks. The analysis is straightforward: We simply test whether the characteristics of the surviving and non-surviving banks were different from each other, on average, at the beginning of the 1997-2012 sample period. These difference-in-means tests are displayed in Tables 2 and 3. Detailed definitions and summary statistics for the business activity and financial performance ratios used in these tests are provided in Appendix Table A1.

Because policymakers are especially interested in whether banks survive during turbulent economic times, we perform the difference-in-means tests for three time periods: The full 1997-2012 sample period, the relatively stable 1997-2006 sub-period, and the relatively stressful 2006-2012 financial crisis sub-period.[16] We mitigate survivor bias in the 2006-2012 sub-period tests by drawing a new sample of 690 banking companies with assets between $500 million and $10 billion at year-end 2006.[17] Within each of these sub-periods, we perform the difference-in-means tests for three different bank size groups: The full sample of banks with $500 million to $10 billion in assets, a subsample of smaller banks with assets between $500 million and $2 billion, and a subsample of larger banks with

[16] It is a coincidence, not a typographical error, that the 1997-2012 sample contains 244 survivors and 302 non-survivors, while the 1997-2006 sub-period contains 302 survivors and 244 non-survivors.

[17] The year-end 2006 sample of 690 banks is drawn using the same sampling techniques and thresholds used to draw the year-end 1997 sample of 546 banks. The 2006 sample contains more banks, chiefly because real asset growth between 1997 and 2006 pushed banks across the $500 million lower bound.

assets between \$2 billion and \$10 billion. In all cases, the difference-in-means tests are based on averages calculated using two years of data just prior to the beginning of the time period in question.[18]

Before proceeding further, we note that difference-in-means tests for the larger \$2 billion to \$10 billion subsample (shown in third rows of each panel in Tables 2 and 3) yield relatively few significant differences between survivor and non-survivor banks. One plausible explanation is that the business activities of banks—and hence the financial performances of banks—become more homogeneous with bank size, leaving less scope for finding material differences across surviving and non-surviving banks. Another plausible explanation is that the small number of observations in this subsample simply reduces statistical precision. For the remainder of this section, we limit our analysis to the full sample of banks (the first row of each panel) and the \$500 million to \$2 billion subsample (the second row of each panel).

4.1. Business activities

Table 2 compares the business activities of survivor and non-survivor banks. We begin with banks' loan portfolios. On average, non-surviving banks were more aggressive lenders, making \$2.79 more *Total Loans* per \$100 of assets than surviving banks (panel 1). This is consistent with a familiar story. Banks can increase their short-term earnings by approving rather than rejecting the marginal loan application, but this aggressive lending strategy can increase credit risk exposure over the longer term.

The composition of banks' loan portfolios also matters. Albeit difficult to quantify, relationship lending is one of the hallmark characteristics of the traditional banking business model. We define *Relationship Loans* (panel 4) as the sum of *Business Loans* (panel 2) and *Household Loans* (panel 3). Business loans includes all commercial and industrial loans that are not secured by real estate; for the relatively small banks in this study, these consist almost entirely of loans to small and privately held businesses for which a close bank-borrower relationship is a given. Household loans includes consumer loans (e.g., credit card, auto, home equity) and residential mortgages; the fact that these loans are held on banks' balance sheets, as opposed to being sold into loan securitizations, is a strong indication that

[18] Using two years of data reduces the impact of unusually high or low one-year values. For the 1997-2012 and 1997-2006 test periods, we calculate the mean averages using year-end 1996 and year-end 1997 data. For the 2006-2012 test period, we calculate the mean averages using year-end 2005 and year-end 2006 data. Using three-year averages does not change the results.

banks seek to maintain or develop a relationship with these borrowers. Thus, the *Relationship Loans* variable is likely associated with a bank's ability to glean useful information from in-person relationships, and as such be associated with positive loan portfolio performance. In contrast, *Real Estate Loans* captures loans made to businesses secured by the value of underlying real estate; this includes commercial real estate loans, construction and development loans, and commercial mortgage loans (panel 5). Fluctuations in local real estate prices have a large influence on the performance of these loans, regardless of whether an in-person relationship exists between the borrower and the bank.

Heading into 2006, banks that ultimately survived the crisis period were holding $4.69 more relationship loans (by our definition) per $100 of assets than banks that did not survive the crisis, but were holding $4.54 fewer real estate-backed loans per $100 of assets.[19] This is consistent with the findings of Cole and White (2012), who show that high concentrations of real estate-backed commercial loans and real estate-backed construction and development loans were positively associated with bank failure during both the financial crisis of 2007-2009 and the bank failure wave of the late 1980s and early 1990s. In contrast, banks that survived the less stressful 1997-2006 period held $2.07 <u>*fewer*</u> relationship loans per $100 of assets—a stark difference that reminds us of a point made earlier, that the financial viability of a business model depends on its ability to withstand external shocks across all phases of the business cycle.

Another hallmark characteristic of the traditional banking model is the use of relationship deposits to fund bank assets. Doing so reduces both funding costs and liquidity risk, because relationship depositors are more likely to maintain high deposit balances even if they are paid a below-market interest rate. We use *Core Deposits* as a proxy for relationship deposits (panel 6). The benefits of this funding approach show up throughout the business cycle but especially during the crisis period. Heading into 1997, banks that survived until 2012 were using $2.71 more core deposits per $100 of

[19] We note that the $4.69 *Relationship Loans* result is driven solely by the *Household Loans* ratio (panel 3); the *Business Loans* ratio (panel 2) is by itself unrelated to survival in any of the time periods in Table 2. This is not surprising. For household lending, a small bank can choose between the traditional relationship-based strategy or the nontraditional loan securitization strategy. But for business lending, all small banks, regardless of strategy, have access only to small business loans, which be definition require a relationship-based approach.

assets than non-survivors; heading into 2006, banks that survived until 2012 were using $6.02 more core deposits per $100 of assets than banks that did not survive the crisis.

By definition, a traditional bank will generate the lion's share of its income from traditional banking activities. *Traditional Fee Income* captures fees received by a bank for providing transactions and safekeeping services to its depositors, and asset management and fiduciary services to wealthy deposit or loan customers (panel 7). Heading into 1997, banks that survived until 2012 were earning $1.78 more traditional fees per $1,000 of assets than non-survivors; heading into 2006, banks that survived until 2012 were earning $2.35 more traditional fees per $1,000 of assets than banks that did not survive the crisis. We find no systematic differences across surviving and non-surviving banks for *Total Traditional Income* (panel 8, traditional fee revenue plus net interest income) or *Total Noninterest Income* (panel 9, traditional fee revenue plus fee revenue from less traditional activities such as investment banking, loan securitization, securities brokerage and insurance sales).

Bank branches are another important feature of the traditional banking model. Brick-and-mortar branches help attract new deposit customers, provide a physical location for servicing both loan and deposit customers, and allow bankers to launch and maintain in-person relationships with their customers. On balance, our data indicate that a wider network of physical branches—which we measure as the number of branches per $1,000 of assets, or *Branch Intensity*—can enhance the long-run stability of a banking enterprise. Surviving banks operated more branches per dollar of assets than non-surviving banks throughout our entire sample period, as well as during both the pre- and post-crisis subsample periods (panel 10).

4.2. Financial performance

Table 3 compares the financial performance of survivor and non-survivor banks. Clearly, one would expect profitability to enhance long-run survival. Heading into 1997, *Return on Assets* was 8 basis points higher for banks that survived until 2012 than for banks that did not survive (panel 11). But heading into 2006, ROA at banks that survived the financial crisis was no larger on average than ROA at banks that did not survive the crisis. This surprising result can be explained by fluctuations in the *Noninterest Expense* ratios across the business cycle (panel 12, noninterest expenses-to-operating income). During normal times, banks that control overhead spending will register higher earnings and will be more likely to survive at the margin. Indeed, heading into the relatively stable 1997-2006 sub-period, noninterest expenses were consuming 1.40% less of the operating income at surviving banks than at non-surviving banks. But during economically stressful times, the benefits of noninterest spending—for example, spending on loan screening and monitoring that reduces credit risk, or spending on branch networks that helps maintain stable low-cost funding—are revealed. Heading into the stressful 2006-2012 sub-period, noninterest expenses were consuming 2.28% more operating income at surviving banks than at non-survivors.

Banks must take on risks in order earn profits, but banks that are better at managing these risks are more likely to survive in the long run. In our data, rapid growth (panel 13, *Asset Growth*), financial leverage (panel 14, *Equity Capital*), ex ante credit risk (panel 15, *Risk-weighted Assets*), ex post credit risk (panel 16, *Nonperforming Loans*), and liquidity risk (panel 17, *Unused Loan Commitments*; panel 18, *Liquid Assets*; and panel 19, *Funding Gap*) are all more closely associated with non-surviving banks than with surviving banks. For all of these variables, we find at least some statistically significant evidence that more conservative risk management is associated with bank survival. For all but one of these variables (*Equity Capital*), the economic magnitudes of these differences are largest heading into the 2006-2012 crisis period.

5. Identifying a traditional bank

In Table 2 we found that business activities that we associate with traditional banking—i.e., relationship loans, core deposits, traditional banking services and physical branches—are individually associated with bank survival. Hence, if a bank has high levels for all four of these activities, one might say that the bank is using a traditional banking model:

1. <u>Relationship lending</u>. A traditional bank aims to establish and maintain long-term relationships with borrowers that last beyond the loan deal currently at hand. These relationships generate soft information about the personal character and creditworthiness of individual household and small business borrowers. Once these lending relationships are established, customers quite often purchase additional financial products and services from the bank. As discussed above, we use the

ratio of commercial loans, consumer loans, and held-in-portfolio residential mortgage loans to total bank assets as our proxy for relationship lending (*Relationship Loans*).

2. Relationship deposits. In the traditional banking model, core deposits are the primary source of funding. These are interest-inelastic deposits made by household and business customers, which makes them ideal for financing the illiquid relationship loans made by traditional banks. The stability of these deposits encourages bank-depositor relationships that are beneficial to the bank in at least two additional ways: Long-run relationships facilitate the transfer of soft information to the bank, and long-run depositors are likely to purchase multiple financial products from the bank. We use the ratio of transactions deposits and small time deposits to total bank assets as our proxy for relationship deposits (*Core Deposits*).
3. Traditional activities. Interest income is the primary source of revenue at a traditional commercial bank, but it is supplemented by fees the bank earns from providing noninterest financial services to its relationship banking customers. The two most traditional sources of these noninterest revenues are fees collected by the bank in exchange for providing payments services for its transactions depositors (e.g., minimum balance fees, overdraft fees) and fees collected by the bank in exchange for managing the assets of its wealthier business and household clients (i.e., fiduciary services). While modern banking companies often engage in the provision of a wide range of other financial services (e.g., investment banking, venture capital, securities brokerage, insurance underwriting), these services lay largely outside the boundaries of the traditional banking model. As our proxy for traditional activities, we use the ratio of net interest income plus traditional fee income to total bank assets (*Total Traditional Income*).
4. Branch networks. Physical bank branches facilitate the person-to-person contact necessary for relationship lending and relationship deposit-taking. While traditional banks augment their branch delivery systems with online banking, automated bill pay, mobile banking and other channels, the physical branches remain central to the model because this is where the repeated personal interactions necessary to build and sustain long-lasting relationships most often occur.[20] We

[20] As advances in communications technologies make truly in-person relationships possible without physical proximity, bank branches may become a less necessary component for relationship banking.

measure the intensity of the branch banking network as the number of bank branches divided by total bank assets (*Branch Intensity*).

We identify a bank that is using a traditional banking model as follows: If a bank exceeds the sample median (50th percentile) for at least three of the above four attributes, then we declare it to be *traditional*. If a bank exceeds the sample median value for at most one of the above four attributes, then we declare it to be *nontraditional*. If a bank satisfies neither of these definitions, then we declare it to be *strategically ambiguous*. We calculate all of the median values using two years of data. Based on 1996-97 sample medians, we identify 193 traditional banks, 188 nontraditional banks, and 165 strategically ambiguous banks heading into the 1997-2012 time period. Based on 2005-06 sample medians, we identify 241 traditional banks, 251 nontraditional banks, and 198 strategically ambiguous banks heading into the 2006-2012 sub-period.

These business strategies were quite stable over these two sub-periods: 77.4% of the traditional banks at the beginning of the 2006-2012 sub-period started out as traditional banks in 1997, and 81.6% of the non-traditional banks at the beginning of the 2006-2012 sub-period started out as non-traditional banks in 1997. A high degree of stability can also be inferred from Figure 2, which plots the median values for each of the four hallmark traditional bank characteristics during each year of our data.

The analysis in Table 4 is in the spirit of Stigler's (1958) simple survivorship concept. We discard the strategically ambiguous banks, and then compare the survival rates of the traditional and nontraditional banks. Traditional banks were 7.8 percentage points more likely than their non-traditional peers to survive from the beginning to the end of the full 1997-2012 sample period (top panel). This translates into a 19.2% survival advantage. This result is driven by the small traditional banks with assets less than $2 billion, which were 9.7 percentage points more likely to survive through the end of the sample period, for a 24.2% survival advantage. We find no evidence that the larger traditional banks with assets between $2 billion and $10 billion enjoyed a survival advantage—or a survival disadvantage—across the full sample period.

An important result emerges when we separate our analysis into the 1997-2006 and 2007-2012 sub-periods. For the economically 'normal' 1997-2006 period (middle panel), the results are both economically and statistically similar to the results for the full sample period. But the results are both qualitatively and quantitatively stronger during the more stressful 2007-2012 'crisis' period (bottom panel). The mean survival differences between traditional and non-traditional banks (column 5) are substantially larger, are more statistically precise, and now hold for both the smaller and larger bank subsamples. The smaller traditional banks were 16.3 percentage points more likely to survive through the crisis period, and the larger traditional banks were 21.1 percentage points more likely to survive through the crisis period, than their non-traditional peers.

6. Multivariate survival analysis

To better estimate the impact of traditional banking on bank survival, we now move to a multivariate model. Our data set contains 6,888 different banks, with as many as 16 annual observations each, and we would like to exploit as much of the variation in these data as possible. However, fixed effects panel estimation is problematic in binary outcome (e.g., survival versus failure) models. Probit and logit models with firm fixed effects do not generate consistent parameter estimates, and probit and logit models with random effects impose a distribution on the unobservable firm effects and requires them to be independent of the other regressors (Wooldridge 2010, pages 608-625). Using an OLS linear probability model would avoid these issues, but it is highly unlikely that the true relationship between survival and the nontraditional banking is linear. Given all this, we use a pooled probit approach with time fixed effects and a first-stage Heckman correction. The model takes the following general form:

$$\begin{aligned} \mathit{Prob}_{i,t}(\mathit{survived\ year\ t}) = a + b{*}\mathit{Traditional\ Index}_{i,t\text{-}1} \\ + c{*}Z_{i,t\text{-}1} + d{*}\mathit{Inverse\ Mills\ Ratio}_{i,t\text{-}1} + \tau_t + e_{i,t} \end{aligned} \tag{1}$$

where *i* indexes banks, *t* indexes years, and τ_t are year fixed effects. The dependent variable $\mathit{Prob}_{i,t}(\mathit{survived\ year\ t})$ is specified as a dummy equal to one if bank *i* survived from the end of year *t*-1 through the end of year *t*. In our initial probit estimations, we (a) define survival as not failing, not being voluntarily liquidated, and not being acquired by another banking company, and (b) we include only banks with assets greater than \$500 million in our analysis. In subsequent estimations of the model we relax both of these restrictions.

The main test variable is *Traditional Index*, which is equal to the percentage of the four traditional bank attributes (*Relationship Loans*, *Core Deposits*, *Traditional Income*, *Branch Intensity*) for which bank i exceeds the annual sample median in year t-1. This index ranges from a low of 0 for a fully nontraditional bank to a high of 100 for a fully traditional bank. The *Traditional Index* variable has two advantages over the dichotomous 'traditional versus non-traditional' approach taken in Table 4: It is a continuous measure that better captures the intensity with which a bank practices a traditional banking business model, and it allows us to retain the strategically ambiguous banks which account for about 30% (165/546) of the banking companies in our sample.

We also include a Z vector of 15 control variables likely to be associated with bank survival. These variables measure bank-specific and local market-specific characteristics and conditions, all but one of which are time-varying. We provide definitions and summary statistics for all of these variables in Appendix Table A2.

Finally, we employ a first-stage Heckman (1979) selection procedure to control for potential bias caused by restricting our sample to banks with assets between \$500 million and \$10 billion.[21] We include three instruments in the selection equation: The population in each bank's home state (*Population*); GDP per capita in each bank's home state (*Per Capita GDP*); and the age of the bank (*Age*). We are mainly concerned about the selection effect caused by excluding small banks, because well over 90% of US banking companies had assets less than \$500 million at the start of our sample period. A priori, size-based selection is more likely to result in bias in more heavily populated markets (*Population*) and/or in economically vibrant markets (*Per Capita GDP*) in which small banks have greater opportunities to grow larger and clear the \$500 million threshold. We have no a priori expectation regarding bank age: On the one hand, an older bank has had more time to accumulate

[21] We use a first-stage probit model to estimate the probability of observing a banking company with assets between \$500 million and \$10 billion from among all banking companies in the industry population. We then use the estimated parameters from this model to calculate the inverse Mills ratio, defined as the ratio of the probability density function over the cumulative distribution function of the distribution. The inverse Mills ratio is then included as an additional explanatory variable in the second-stage estimation (i.e., our equation 1).

assets. On the other hand, a substantial percentage of US banking companies at the beginning of our sample period were small, risk averse, older franchises that were less likely to exit the industry via either failure or acquisition.

The first-stage Heckman results are displayed in Appendix Table A3. All three of our excluded instruments carry statistically significant coefficients. As expected, the coefficients on *Population* and *Per Capita GDP* are positive. The negative coefficient on *Age* suggests that many of the oldest US commercial banks in 1997 started out small and stayed that way.

6.1. Baseline results

Table 5 displays results for equation (1), estimated using a pooled probit model with time fixed effects for the 546 banks with assets between \$500 million and \$10 billion in 1997. Columns 1 and 2 use the full data sample. Columns 3 and 4 use subsamples of banks smaller and larger than the \$2 billion threshold discussed above.[22] In all columns, the cells display marginal probabilities (rather than raw coefficient estimates). Z-statistics for the raw probit coefficients appear in parentheses and are based on standard errors clustered at the bank level.

The coefficient on the *Inverse Mills Ratio* is statistically significant in all but one of the models, an indication that selection bias exists and that our two-stage procedure has corrected at least partially for this bias. The positive sign on this coefficient suggests that banks with a higher probability of being selected into our sample—that is, relatively younger banks (*Age*) in wealthier (*Per Capita GDP*) and more heavily populated (*Population*) places—were more likely to survive the 1997-2012 sample period than the predominantly smaller banks that we excluded from our sample.

The coefficients on *Traditional Index* provide our main tests. We find a statistically positive and economically substantial relationship between traditional banking and bank survival. This survival advantage is limited to banks with assets less than \$2 billion, and disappears in the subsample of larger banks in column 4. Based on the full sample results in column 2, a one percentage point increase in *Traditional Index* around its sample mean is associated with a 12 basis point increase in the probability of a bank surviving for one additional year, after controlling for all other specified factors. As displayed

[22] An additional subsample estimation for banks with assets between \$500 million to \$1 billion (not shown) yielded results nearly identical to the \$500 million to \$2 billion subsample regression.

in Figure 3, a marginally traditional bank (*Traditional Index* = 75) had an estimated 6 percentage point higher probability of surviving for one additional year than a marginally nontraditional bank (*Traditional Index* = 25). As displayed in Figure 4, marginally traditional banks were an estimated 13 percentage points more likely to survive across the entire 1997-2012 sample period than marginally nontraditional banks.

Eleven of the fifteen control variables have statistically significant coefficients in at least one of the models in Table 5. Credit risk continues to be a strong indicator of bank survival: *Risk-weighted Assets*, *Nonperforming Loans*, and *Loan Concentration* are all statistically and negatively associated with survival. Holding a larger cushion against these risks is positively associated with bank survival, as indicated by the coefficients on *Risk-based Equity Capital*. Not surprisingly, after controlling for credit risk and insolvency risk, more profitable banks (*Return on Assets*) are statistically more likely to survive. Operating efficiency also matters, as increases in *Noninterest Expense* significantly reduce banks' survival chances. Banks that book larger amounts of *Goodwill* are less likely to survive.

6.2. Strategic failures versus financial failures

Our methodology is based on our Stiglerian assertion that bank survival indicates bank efficiency. Moreover, we argue even more strictly that bank exit indicates bank inefficiency regardless of whether the bank exited via insolvency or acquisition. It should be non-controversial that insolvency (exit via financial failure) indicates some kind of inefficiency relative to banks that remained solvent; however, it is less clear that being acquired (exit via strategic failure) necessarily indicates that a community bank is inefficient relative to banks that were not acquired. To investigate this potential methodological shortcoming, we re-estimate our Table 5 tests using a multinomial probit model that separately specifies strategic failure and financial failure. The dependent variable equals 0 if bank *i* survived from the end of year *t-1* through the end of year *t*, equals 1 if the bank *i* did not survive due to a strategic failure, and equals 2 if the bank *i* did not survive due to a financial failure.

Table 6 displays partial results from the multinomial probit estimations. Once again, we find a positive relationship between the traditional banking model and bank survival, with marginal effects similar in magnitude to those from the binomial specification in Table 5, and once again limited to banks with assets less than $2 billion. More to the point, we find that traditional banking has statistically negative effects on both strategic failure and financial failure and, importantly, that the economic magnitudes of these two effects are very similar. Based on the full sample estimates in column 1, a one percentage point increase in *Traditional Index* around its sample mean is associated with a 7 basis point reduction in the intra-year probability of strategic failure, and a 6 basis point reduction in the intra-year probability of financial failure. (By necessity, these two marginal effects sum to 13 basis points, the marginal increase in survival associated with *Traditional Index*.) These marginal effects approximately double in column 2 for the subsample that excludes very large community banks.

These results are consistent with our maintained assumption that bank exit, regardless of exit channel, is indicative of bank inefficiency. Our estimates indicate that the efficiency-enhancing qualities of the traditional banking business model increase the likelihood of community bank survival, and this occurs via equal reductions in the likelihoods of bank failure and bank acquisition. An economically intuitive way to interpret these results: If two community banks are potential acquisition targets, the more efficient (profitable) of the two banks will naturally have the higher reservation price. Because we know that the traditional banking model is efficiency-enhancing (i.e., our data show that traditional banks are less likely to fail), non-traditional banks will be relatively less efficient, have lower reservation prices, and hence be more likely to exit via acquisition.

6.3. Banks with assets less than $500 million

We have thus far excluded banks with assets less than $500 million from our analysis. The raw data in Figure 1 show that this sector of the US banking industry has shrunk dramatically over the past two decades, and evidence from the bank cost function literature (McAllister and McManus 1993, Wheelock and Wilson 2001) suggests this shrinkage was due to the suboptimal scale of these banks. We argue above that any group of banks with systematic inefficiencies (be they scale, technical, or allocative inefficiencies) would be less able to successfully implement the traditional banking model (or indeed, any business model) in a competitive banking market. Because of this, including these banks in our data could bias our findings.

We now investigate further. We use our binomial pooled probit model to estimate equation (1) for various subsamples of banks with assets less than $500 million. Finding $b>0$ in these tests would indicate that the competitive advantages of the traditional banking model are so strong that they more than offset the size-based efficiency disadvantages of these banks. Figure 5 plots the *b* coefficients, along with 95% confidence intervals, estimated for subsamples of banks with assets between \$100 and \$200 million, \$200 to \$300 million, and \$300 to \$500 million. We also include *b* from the full sample of banks with assets between \$500 million to \$10 billion sample (Table 5, column 2).

The results suggest that the size disadvantages of small banks overwhelm the competitive advantages of the traditional banking model. For banks with assets less than \$300 million, estimated *b* is essentially zero. For banks with assets between \$300 and \$500 million, estimated *b* is positive but not statistically different from zero.

7. The traditional banking model during the financial crisis

It is natural to ask whether the superior survivability of the traditional banking model manifests itself more strongly under normal economic conditions or during stressful times such as the financial crisis. Our simple difference-in-means analysis in Table 4 suggests the latter, and we now pursue this question in greater detail. We re-specify the right-hand side of equation (1) as:

$$\begin{aligned} Prob_{i,t}(survived\ year\ t) = {} & a + b_{crisis}{*}Traditional\ Index_{i,t-1}{*}Crisis \\ & + b_{no\ crisis}{*}Traditional\ Index_{i,t-1}{*}(1\text{-}Crisis) + c{*}Z_{i,t-1} + d{*}Inverse\ Mills\ Ratio_{i,t-1} + e_{i,t} \end{aligned} \tag{2}$$

where the single test variable *Traditional Index* is replaced with a pair of test variables *Traditional Index*Crisis* and *Traditional Index*(1 – Crisis),* where *Crisis* is a dummy variable equal to one in years 2008 through 2012.[23] We exclude year fixed effects from this specification.

The results are displayed in Table 7, and they indicate that the survivability advantage associated with traditional banking was approximately twice as large during the crisis years. Based on the full sample estimates in column 1, a one percentage point increase in *Traditional Index* around its sample mean is associated with a 25 basis point increase in the probability that a bank would survive one additional year during the 2008-2012 crisis period, but only an 11 basis point increase during the

[23] Our results are strongly robust to redefining *Crisis* to equal 1 for 2008-2010.

less stressful 1997-2007 pre-crisis years. A Wald test rejects the null hypothesis that the coefficient on *Traditional Index*Crisis* is equal to the coefficient on *Traditional Index*(1 – Crisis)*.

As in our earlier tests, we find stronger evidence of a traditional banking survival advantage for the banks in the $500 million to $2 billion subsample. Moreover, in the more flexible equation (2) specification, we now find sensible and statistically significant results for two of the more important control variables. The chance of survival should improve with the strength of local economic conditions; *State Credit Quality*, a deposit-weighted average of overall nonperforming loan conditions in the states in which each bank operates, now carries the expected statistically negative coefficient. All else equal, larger community banks should have a survival advantage over smaller community banks; the coefficient on *lnAssets*, a standard measure of bank size in empirical banking research, now carries the expected statistically positive coefficient.

In Figure 5, panels B and C show the results of equation (2) when estimated for subsamples of banks with assets less than $500 million. During normal (*no crisis*) years, the size disadvantage of being very small overwhelms the competitive advantages of the traditional banking model. But during *crisis* years, the data indicate that the traditional banking model more than offset the size disadvantage for banks with assets between $300 and $500 million, at the margin making them more likely to survive.

8. Robustness tests

We determine whether a bank is using a traditional business model by comparing its values for *Relationship Loans, Core Deposits, Traditional Income*, and *Branch Intensity* in year *t* to the sample median (50th percentile) values for these variables in year *t*. Because it is clearly arbitrary to make this distinction based on the 50th percentile of the sample distributions, we re-calculated *Traditional Index* based on the 30th, 40th, 60th and 70th percentiles, and then re-estimated equations (1) and (2) using these values. Table 8 displays partial results from these re-estimations. The results are remarkably stable across panels A through E, with no changes in coefficient signs or statistical significance, and only trivial changes in the absolute and relative coefficient magnitudes. Importantly, the range of variation in these definition benchmarks—from the 30th percentiles to the 70th percentiles—far outstrips the variation over time in the median values for any of the four hallmark characteristics shown in Figure 2.

The results of the multinomial probit estimations in Table 6, along with our interpretation of those results, are consistent with an efficient market for external corporate control in which marginally more (less) inefficient banks are more (less) likely to be acquired. We also test whether and how differences in internal control conditions influence our results. We re-estimate equations (1) and (2) after conditioning these models on a *Subchapter S Bank* dummy (closely held banks that theoretically should exhibit strong corporate governance) and a *Multi-bank Holding Company* dummy (organizationally complex banks that theoretically should be more difficult to govern). As shown in Table 9, the coefficients on these variables carry the theoretically expected signs, but neither is statistically significant.

As discussed above, we estimated equations (1) and (2) using pooled binomial or pooled multinomial probit models with year fixed effects and first-stage Heckman corrections. For our final robustness tests, we re-estimate our models using alternative statistical approaches. Partial results (marginal effects) are displayed in Table 10, where panel A shows our baseline results, and panels B through D show results from the alternative models. The marginal effects on the *Traditional Index* variables have the same signs and are statistically significant throughout. Although the magnitudes of these effects are smaller, they remain economically meaningful. Based on the smallest of these estimates (panel B, column 1), we calculate that marginally traditional banks (*Traditional Index* = 75) were an estimated 8 percentage points more likely to survive across the entire 1997-2012 sample period than marginally nontraditional banks (*Traditional Index* = 25).

9. Conclusions

A multitude of papers and books have investigated the role of, and the consequences for, commercial banks during the global financial crisis of 2007-2009. The implicit underlying question in nearly all of these studies is "What went wrong?" In this study, we attempt to gain new insights by turning this question around, instead asking "What went right?" We identify a set of small US banks—so-called community banks—that survived the financial crisis, and test whether strict adherence to traditional banking practices played a role in their survival.

The concept of survivorship was first introduced by Stigler (1958) and we adapt it for our own unique purposes here. We label a bank to be a survivor if it did not fail, and was not acquired by another bank, during our 1997 to 2012 sample period. In other words, we recognize that non-survival can occur not just for financial reasons (for example, a bank becomes insolvent or illiquid), but also for strategic reasons (for example, a bank has a bad business model and/or it executes its business model poorly, and as a result disappears in the market for corporate control). We measure the degree to which surviving and non-surviving banks were using traditional business models based on four hallmark characteristics of traditional commercial banking: Relationship lending, core deposit funding, revenues generated from traditional banking services, and intensive use of bank branches. We focus our analysis on banks with assets between \$500 million and \$10 billion, that is, banks that are large enough to capture the bulk of the scale economies available in the traditional business model, but still too small to fully exploit the production efficiencies available in a more modern transactions-type business model.

Our most basic survivor analysis, and the one most reminiscent of Stigler (1958), is a straightforward difference-in-proportions test. We simply observe whether banks with highly traditional business models were more or less likely to survive (by our definition) from 1997 through 2012 compared to banks with largely nontraditional business models. In these tests, the traditional banks were about 19% more likely to survive on average than the nontraditional banks. Limiting our analysis to the shorter but more stressful 2006-2012 time period, this traditional bank survival advantage increases to about 23%.

At the other methodological extreme, we estimate multivariate models of bank survival using annual 1997-2012 data for each bank. Our main model is pooled probit model with year fixed effects, clustered standard errors, a first-stage Heckman correction, and numerous control variables for bank attributes, local economic conditions, and local competitive conditions. On average, a bank that adhered closely to the traditional business model—more exactly, a bank that satisfied at least three of the four hallmark characteristics of traditional banking, relative to a bank that satisfied at most one of these four characteristics—increased its chance of surviving an additional year by an estimated 6 percentage points, and increased its chance of surviving the entire sample period by an estimated 13 percentage points. Using alternative specifications, we find that this traditional bank survival advantage approximately doubled during the financial crisis.

The population of community banks in the US has been in steep decline for two decades. While this decline has likely not yet run its full course, our results suggest that industry consolidation will not result in the complete extinction of community banks. Our results show that community banks adhering to the traditional banking business model have proven to be more resilient than other community banks under both normal and stressful economic conditions. Thus, we draw the following conditional conclusion: The traditional community bank business model has been and can be strategically viable, so long as this business model is applied to a bank of adequate and appropriate scale. But two important caveats are in order. First, our findings are based on a pre-Basel III, pre-Dodd-Frank regulatory regime. Going forward, the fixed costs of complying with increasing stringent supervision and regulation may weigh disproportionately on small banks, and erode the survivability advantages of the traditional community banking model revealed in our estimates. Second, our findings are based on competitive advantages using the information and communications technologies that existed during our 1997-2012 data period. Going forward, technological change may allow large banking organizations to approximate the soft-information, personal relationship banking approaches here-to-for available only at small banks, and erode the competitive advantages of the traditional banking model.

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Table 1

This table displays changes in the population of US commercial banks (bank holding companies plus stand-alone commercial banks) between year-end 1997 and year-end 2012. The upper panel contains data for the population of banks. The lower panel contains data for banks with between $500 million and $10 billion. A "surviving bank" was still in operation at year-end 2012. A "non-surviving" bank was no longer in operation at year-end 2012.

	Distribution of surviving and non-surviving banks	Distribution of non-surviving banks
All US commercial banks at year-end 1997:	9,050	
After applying data filters:	6,888 (100.0%)	
Survived until year-end 2012:	4,164 (60.5%)	
Did not survive through year-end 2012:	2,724 (39.5%)	2,724 (100.0%)
Healthy banks acquired in M&A:		2,341 (85.9%)
Failed banks seized by FDIC:		281 (10.3%)
Voluntarily closed or liquidated:		73 (2.7%)
Would have failed without TARP injection:		3 (0.1%)
Other:		26 (1.0%)
US commercial banks with assets between $500 million and $10 billion at year-end 1997 after applying data filters:	546 (100.0%)	
Survived until year-end 2012:	244 (44.7%)	
Did not survive through year-end 2012:	302 (55.3%)	302 (100.0%)
Healthy banks acquired in M&A:		252 (83.4%)
Failed banks seized by FDIC:		19 (6.3%)
Voluntarily closed or liquidated:		15 (5.0%)
Would have failed without TARP injection:		0 (0.0%)
Other:		16 (5.3%)

Table 2

This table displays subsample averages of various business model ratios for survivor and non-survivor banks with assets between $500 million and $10 billion. Standard difference-in-means tests are applied across three separate time periods: For 546 banks at the start of the 1997-2012 time period; for 546 banks at the start of the 1997-2006 time period; and for 690 banks at the start of the 2006-2012 time period. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

		1997-2012			**1997-2006**			**2006-2012**		
	size range	**244 Survivors**	**302 Non-survivors**	**Diff.**	**302 Survivors**	**244 Non-survivors**	**Diff.**	**550 Survivors**	**140 Non-survivors**	**Diff.**
1. *Total Loans*	$500M-$10B	60.99	63.78	-2.79***	61.75	63.51	-1.76*	68.27	71.29	-3.02**
(% of Assets)	$500M-$2B	61.11	63.80	-2.69**	61.67	63.73	-2.06**	68.59	72.04	-3.44**
	$2B-$10B	60.52	63.70	-3.18	62.05	62.64	-0.60	66.74	68.16	-1.42
2. *Business Loans*	$500M-$10B	9.51	10.08	-0.57	9.63	10.07	-0.44	9.45	9.44	0.01
(% of Assets)	$500M-$2B	9.16	10.19	-1.03*	9.41	10.13	-0.71	9.17	9.63	-0.46
	$2B-$10B	10.97	9.61	1.36	10.51	9.83	0.68	10.79	8.64	2.15*
3. *Household Loans*	$500M-$10B	33.87	35.38	-1.51	33.97	35.60	-1.63	26.24	21.56	4.68***
(% of Assets)	$500M-$2B	33.87	34.77	-0.90	33.77	35.11	-1.35	26.46	20.97	5.50***
	$2B-$10B	33.85	37.77	-3.92	34.82	37.56	-2.74	25.16	24.03	1.13
4. *Relationship Loans*	$500M-$10B	43.38	45.45	-2.07**	43.60	45.67	-2.07**	35.69	31.00	4.69***
(% of Assets)	$500M-$2B	43.03	44.96	-1.93*	43.18	45.24	-2.06*	35.64	30.60	5.04***
	$2B-$10B	44.82	47.38	-2.56	45.33	47.39	-2.06	35.96	32.68	3.28*
5. *Real Estate Loans*	$500M-$10B	40.10	41.97	-1.88*	40.95	41.37	-0.42	51.86	56.39	-4.54***
(% of Assets)	$500M-$2B	41.11	42.24	-1.13	41.50	42.02	-0.52	52.52	57.01	-4.49***
	$2B-$10B	35.86	40.93	-5.07**	38.68	38.78	-0.09	48.67	53.79	-5.12*
6. *Core Deposits*	$500M-$10B	72.74	70.03	2.71***	72.46	39.74	2.72***	63.56	57.54	6.02***
(% of Assets)	$500M-$2B	73.05	69.45	3.60***	72.63	69.11	3.53***	63.81	58.11	5.70***
	$2B-$10B	70.80	66.70	4.10**	70.14	66.48	3.66**	62.38	55.16	7.22***
7. *Traditional Fee Income*	$500M-$10B	10.18	8.40	1.78*	9.75	8.52	1.22	9.83	7.48	2.35***
(per $1,000 of Assets)	$500M-$2B	10.57	7.87	2.70**	9.97	7.98	1.98*	9.91	7.17	2.73***
	$2B-$10B	8.56	10.53	-1.97	8.84	10.68	-1.84	9.46	8.75	0.72
8. *Total Traditional Income*	$500M-$10B	49.09	48.18	0.91	49.13	47.91	1.22	45.04	44.37	0.67
(per $1,000 of Assets)	$500M-$2B	49.27	47.57	1.70	49.32	47.09	2.23	45.08	44.78	0.30
	$2B-$10B	48.36	50.61	-2.25	48.34	51.18	-2.84	44.83	42.68	2.15
9. *Total Noninterest Income*	$500M-$10B	11.84	10.12	1.72	11.44	10.20	1.24	12.27	9.68	2.59
(per $1,000 of Assets)	$500M-$2B	12.13	9.23	2.90**	11.58	9.23	2.34*	12.41	9.41	3.00
	$2B-$10B	10.65	13.64	-2.99*	10.90	14.08	-3.17	11.56	10.77	0.79
10. *Number of Branches*	$500M-$10B	0.022	0.019	0.003***	0.022	0.019	0.003***	0.019	0.015	0.003***
(per $1,000 of Assets)	$500M-$2B	0.023	0.020	0.003***	0.023	0.020	0.003***	0.019	0.016	0.003***
	$2B-$10B	0.020	0.017	0.003*	0.019	0.017	0.001	0.016	0.013	0.004**

Table 3

This table displays subsample averages of various financial performance ratios for survivor and non-survivor banks with assets between $500 million and $10 billion. Standard difference-in-means tests are applied across three separate time periods: For 546 banks at the start of the 1997-2012 time period; for 546 banks at the start of the 1997-2006 time period; and for 690 banks at the start of the 2006-2012 time period. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

		1997-2012			1997-2006			2006-2012		
	size range	**244 Survivors**	**302 Non-survivors**	**Diff.**	**302 Survivors**	**244 Non-survivors**	**Diff.**	**550 Survivors**	**140 Non-survivors**	**Diff.**
11. *Return on Assets*	$500M-$10B	1.17	1.09	0.08**	1.17	1.07	0.10***	1.18	1.16	0.02
	$500M-$2B	1.17	1.08	0.10***	1.17	1.06	0.11***	1.17	1.17	0.00
	$2B-$10B	1.16	1.17	-0.01	1.18	1.15	0.03	1.23	1.12	0.11
12. *Noninterest Expense*	$500M-$10B	60.75	60.78	-0.03	60.14	61.54	-1.40*	62.47	60.19	2.28*
(% of Operating Income)	$500M-$2B	61.08	61.01	0.07	60.41	61.83	-1.42*	63.15	60.88	2.27*
	$2B-$10B	59.36	59.88	-0.52	59.04	60.38	-1.34	59.23	57.29	1.94
13. *Asset Growth*	$500M-$10B	54.25	66.61	-12.35**	57.73	65.22	-7.50*	36.04	59.12	-23.08***
(%, 1994-1997)	$500M-$2B	54.39	64.67	-10.28**	56.13	64.95	-8.83*	35.28	59.59	-24.31***
	$2B-$10B	53.65	74.02	-20.37**	64.28	66.26	-1.99	39.70	57.17	-17.46*
14. *Equity Capital*	$500M-$10B	15.30	13.39	1.91***	15.17	13.09	2.08***	13.21	12.35	0.87
(% of Risk-weighted Assets)	$500M-$2B	15.61	13.38	2.23***	15.53	12.95	2.58***	13.31	12.60	0.71
	$2B-$10B	14.01	13.42	0.59	13.68	13.67	0.01	12.75	11.30	1.45**
15. *Risk-weighted Assets*	$500M-$10B	62.64	65.70	-3.06***	65.13	65.81	-2.68***	73.42	77.59	-4.17***
(% of Assets)	$500M-$2B	62.46	65.68	-3.22***	62.87	65.93	-3.06***	73.42	77.78	-4.36***
	$2B-$10B	63.37	65.77	-2.41	64.22	65.33	-1.11	73.38	76.80	-3.41*
16. *Nonperforming Loans*	$500M-$10B	0.59	0.62	-0.03	0.60	0.63	-0.03	0.42	0.52	-0.09*
(% of Assets)	$500M-$2B	0.60	0.61	-0.01	0.59	0.63	-0.04	0.44	0.54	-0.10*
	$2B-$10B	0.55	0.67	-0.12*	0.62	0.62	0.00	0.34	0.44	-0.09*
17. *Unused Loan Commitments*	$500M-$10B	0.13	0.14	-0.01	0.13	0.14	-0.01*	0.17	0.19	-0.03***
(% of Assets)	$500M-$2B	0.12	0.13	-0.01**	0.12	0.13	-0.01**	0.16	0.19	-0.03***
	$2B-$10B	0.18	0.16	0.02	0.17	0.17	0.01	0.20	0.21	-0.02
18. *Liquid Assets*	$500M-$10B	25.59	25.29	0.29	25.05	25.88	-0.83	24.06	20.84	3.23**
(% of Liabilities)	$500M-$2B	25.86	25.51	0.35	25.23	26.20	-0.97	24.06	20.41	3.66**
	$2B-$10B	24.46	24.45	0.02	24.32	24.61	-0.29	24.07	22.65	1.42
19. *Funding Gap*	$500M-$10B	72.83	78.42	-5.58***	73.91	78.41	-4.50***	85.82	94.00	-8.19***
(Loans as % of Deposits)	$500M-$2B	72.66	78.00	-5.34***	73.48	78.24	-4.76***	85.79	93.76	-7.97***
	$2B-$10B	73.55	80.07	-6.52**	75.69	79.10	-3.41	85.95	95.02	-9.06**

Table 4

This table compares the survival rates of traditional and nontraditional banks with assets between $500 million and $10 billion. Standard difference-in-means tests are applied across three separate time periods: For 381 banks at the start of the 1997-2012 time period; for 381 banks at the start of the 1997-2006 time period; and for 492 banks at the start of the 2006-2012 time period. A "traditional bank" satisfies at least three of the following four criteria: (1) relationship loans/assets > median sample value; (2) core deposits/assets > median sample value; (3) traditional income/assets > median sample value; and (4) branches/assets > median sample value. A "nontraditional bank" satisfies at most one of the above four criteria.

	[1]	[2]	[3]	[4]	[5]	[6]
			1997-2012			
	traditional banks	**nontraditional banks**	**% traditional banks survived**	**% nontraditional banks survived**	**Difference [3] – [4]**	**Survival advantage ([3] – [4]) / [4]**
$500 million to $10 billion	193	188	48.2%	40.4%	7.8%*	19.2%
$500 million to $2 billion	155	155	49.7%	40.0%	9.7%**	24.2%
$2 billion to $10 billion	39	36	46.2%	41.7%	4.5%	10.8%
			1997-2006			
	traditional banks	**nontraditional banks**	**% traditional banks survived**	**% nontraditional banks survived**	**Difference [3] – [4]**	**Survival advantage ([3] – [4]) / [4]**
$500 million to $10 billion	193	188	57.5%	49.5%	8.0%*	16.3%
$500 million to $2 billion	155	155	59.4%	49.7%	9.7%**	19.5%
$2 billion to $10 billion	39	36	51.3%	52.8%	-1.5%	-2.8%
			2006-2012			
	traditional banks	**nontraditional banks**	**% traditional banks survived**	**% nontraditional banks survived**	**Difference [3] – [4]**	**Survival advantage ([3] – [4]) / [4]**
$500 million to $10 billion	241	251	88.8%	72.5%	16.3%***	22.5%
$500 million to $2 billion	198	208	88.9%	72.6%	16.3%***	22.4%
$2 billion to $10 billion	44	43	90.9%	69.8%	21.1%***	30.3%

Note: Because we apply our "three out of four criteria" test independently to each row of data, the numbers in the "traditional banks" and "nontraditional banks" columns do not add up (e.g., 193 ≠ 39 + 155).

Table 5

This table displays the results for equation (1) estimated using a pooled probit model with year fixed effects and a first-stage Heckman correction. The cells display the estimated marginal probabilities. *Z*-statistics for the raw probit coefficients appear in parentheses and are based on standard errors clustered at the bank level. Data for banks with assets between $500 million and $10 billion at the start of the 1997-2012 time period. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Sample:	[1] $500M to $10B	[2] $500M to $10B	[3] $500M to $2B	[4] $2B to $10B
Traditional index	0.0006**	0.0012**	0.0019**	-0.0002
	(2.56)	(2.25)	(2.18)	(-0.48)
State Credit Quality	0.0003	0.0007	-0.0036	0.0082
	(0.08)	(0.09)	(-0.31)	(0.85)
lnAssets	-0.0004	0.0040	-0.0036	-0.0107
	(-0.12)	(1.63)	(-0.28)	(-1.31)
Risk-weighted Assets	-0.0009***	-0.0026***	-0.0051***	0.0004
	(-2.89)	(-3.39)	(-4.16)	(0.73)
Nonperforming Loans	-0.0056**	-0.0127**	-0.0109	-0.0093*
	(-2.44)	(-2.40)	(-1.52)	(-1.88)
Loan Concentration	-0.0458***	-0.1553***	-0.2438***	-0.0577*
	(-2.65)	(-3.24)	(-2.98)	(-1.80)
Commercial Real Estate Loans	0.0003	0.0014	0.0030*	0.0005
	(0.68)	(1.40)	(1.77)	(0.61)
Construction and Development Loans	0.0006	0.0014	0.0018	-0.0004
	(0.92)	(1.02)	(0.82)	(-0.42)
Goodwill	-0.0044**	-0.0035	0.0020	-0.0070**
	(-2.19)	(-0.58)	(0.18)	(-2.38)
Risk-based Equity Capital	0.0065***	0.0125***	0.0178**	0.0033
	(4.03)	(3.04)	(2.50)	(1.13)
Funding Gap	0.0000	0.0007	0.0020**	-0.0002
	(0.19)	(1.32)	(1.99)	(-0.61)
Noninterest Expense	-0.0002	-0.0014*	-0.0023*	-0.0009*
	(-0.90)	(-1.86)	(-1.84)	(-1.84)
Return on Assets	0.0058**	0.0113	0.0163	0.0016
	(2.02)	(1.61)	(1.63)	(0.20)
HHI	-0.0223	-0.1090	0.0386	-0.1065*
	(-0.41)	(-0.88)	(0.17)	(-1.81)
Urban	-0.0064	-0.0187	-0.0032	-0.0054
	(-0.46)	(-0.59)	(-0.03)	(-0.25)
*HHI*Urban*	-0.0380	-0.0369	-0.2081	-0.0001
	(-0.54)	(-0.23)	(-0.69)	(0.02)
Inverse Mills Ratio		0.0242**	0.0329**	0.0069
		(2.36)	(2.43)	(0.55)
Heckman correction	no	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Number of banks/clusters	533	533	428	105
Number of observations	5,094	5,094	4,095	956
pseudo R-squared	0.0774	0.0763	0.0831	0.1346

Table 6

Panel A displays partial results (marginal probabilities) from a pooled multinomial probit model in which the dependent variable specifies three different outcomes: Banks either survived year *t*, suffered strategic failure during year *t*, or financial failure during year *t*. For comparison, panel B repeats the results from the pooled binomial probit estimations in Table 5. All models include a first-stage Heckman selection model, control variables, and year fixed effects. Standard errors are clustered at the bank level. Z-statistics for the raw probit coefficients appear in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Sample:	[1] $500M to $10B	[2] $500M to $2B	[3] $2B to $10B
A: Pooled multinomial probit			
marginal effect of Traditional Index on survival	0.0013***	0.0024**	-0.0013
	(2.83)	(2.09)	(-0.01)
marginal effect of Traditional Index on strategic failure	-0.0007*	-0.0012***	0.0013
	(-1.93)	(-2.59)	(1.06)
marginal effect of Traditional Index on financial failure	-0.0006*	-0.0012**	0.0000
	(-1.66)	(-2.09)	(0.03)
B: Pooled binomial probit (Table 5 results)			
marginal effect of Traditional Index on survival	0.0012**	0.0019**	-0.0002
	(2.25)	(2.18)	(-0.48)

Table 7

This table displays the results for equation (2) estimated using a pooled probit model (without year fixed effects) and a first-stage Heckman correction. *Crisis* = 1 for 2008-2012 and = 0 otherwise. The cells display the estimated marginal probabilities; *Z*-statistics for the raw probit coefficients appear in parentheses and are based on standard errors clustered at the bank level. Data for banks with assets between $500 million and $10 billion at the start of the 1997-2012 time period. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Sample:	[1] $500M to $10B	[2] $500M to $2B	[3] $2B to $10B
*Traditional Index*Crisis*	0.0025***	0.0034***	0.0008
	(4.32)	(3.93)	(1.33)
Traditional Index(1-Crisis)*	0.0011**	0.0018***	-0.0004
	(2.19)	(2.60)	(-0.87)
State Credit Quality	-0.0107**	-0.0142*	-0.0054
	(-2.00)	(-1.91)	(-0.70)
lnAssets	0.0147**	0.0249*	-0.0010
	(2.06)	(1.91)	(-0.08)
Risk-weighted Assets	-0.0021***	-0.0038***	0.0008
	(-3.05)	(-3.78)	(0.96)
Nonperforming Loans	-0.0069*	-0.0042	-0.0078
	(-1.70)	(-0.76)	(-1.25)
Loan Concentration	-0.1068**	-0.1445**	-0.0450
	(-2.48)	(-2.13)	(-0.88)
Commercial Real Estate Loans	0.0017**	0.0027*	0.0018
	(1.99)	(1.94)	(1.35)
Construction and Development Loans	0.0020*	0.0027	-0.0004
	(1.72)	(1.58)	(-0.34)
Goodwill	-0.0040	-0.0023	-0.0106**
	(-0.75)	(-0.30)	(-2.44)
Risk-based Equity Capital	0.0126***	0.0179***	0.0047
	(3.49)	(3.14)	(1.11)
Funding Gap	0.0003	0.0009	-0.0006
	(0.70)	(1.16)	(-1.26)
Noninterest Expense	-0.0007	-0.0008	-0.0008
	(-1.10)	(-0.81)	(-1.06)
Return on Assets	0.0090	0.0128	0.0065
	(1.51)	(1.63)	(0.45)
HHI	-0.0822	0.0590	-0.1534
	(-0.73)	(0.26)	(-1.51)
Urban	-0.0162	-0.0051	-0.0079
	(-0.57)	(-0.11)	(-0.22)
*HHI*Urban*	-0.0628	-0.2127	-0.0189
	(-0.43)	(-0.81)	(-0.10)
Inverse Mills Ratio	0.0243**	0.0331**	0.0067
	(2.39)	(2.46)	(0.53)
Heckman correction	yes	yes	yes
Year fixed effects	no	no	no
Number of banks/clusters	533	428	105
Number of observations	5,094	4,095	956
pseudo R-squared	0.0587	0.0614	0.0922

Table 8

This table displays partial results from robustness tests of equations (1) and (2) estimated using a pooled probit model with year fixed effects and a first-stage Heckman correction. In each panel A through E, the Traditional Index variable is based on a different population benchmark. Left-hand columns contain robustness tests of equation (1), right-hand columns contain robustness tests of equation (2). Cells display the estimated marginal probabilities; *Z*-statistics for the raw probit coefficients appear in parentheses and are based on standard errors clustered at the bank level. Data for banks with assets between $500 million and $10 billion at the start of the 1997-2012 time period. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Sample:	[1] $500M to $10B	[2] $500M to $2B	[3] $2B to $10B	[4] $500M to $10B	[5] $500M to $2B	[6] $2B to $10B
A: *Traditional Index* based on 30th percentiles of the data						
Traditional Index	0.0014**	0.0021**	-0.0001			
	(2.32)	(2.20)	(-0.36)			
*Traditional Index*Crisis*				0.0027***	0.0037***	0.0008
				(4.42)	(4.03)	(1.50)
Traditional Index(1-Crisis)*				0.0011**	0.0019**	-0.0004
				(2.10)	(2.47)	(-0.76)
B: *Traditional Index* based on 40th percentiles of the data						
Traditional Index	0.0013**	0.0020**	-0.0002			
	(2.31)	(2.20)	(-0.43)			
*Traditional Index*Crisis*				0.0026***	0.0036***	0.0008
				(4.45)	(4.06)	(1.34)
Traditional Index(1-Crisis)*				0.0011**	0.0019***	-0.0005
				(2.19)	(2.59)	(-0.92)
C: *Traditional Index* based on 50th percentiles of the data						
Traditional Index	0.0012**	0.0019**	-0.0002			
	(2.25)	(2.18)	(-0.48)			
*Traditional Index*Crisis*				0.0025***	0.0034***	0.0008
				(4.32)	(3.93)	(1.33)
Traditional Index(1-Crisis)*				0.0011**	0.0018***	-0.0004
				(2.19)	(2.60)	(-0.87)
D: *Traditional Index* based on 60th percentiles of the data						
Traditional Index	0.0012**	0.0018**	-0.0002			
	(2.22)	(2.14)	(-0.54)			
*Traditional Index*Crisis*				0.0025***	0.0034***	0.0008
				(4.35)	(3.91)	(1.25)
Traditional Index(1-Crisis)*				0.0010**	0.0017***	-0.0005
				(2.30)	(2.69)	(-1.03)
E: *Traditional Index* based on 70th percentiles of the data						
Traditional Index	0.0011**	0.0017**	-0.0003			
	(2.12)	(2.09)	(-0.82)			
*Traditional Index*Crisis*				0.0025***	0.0033***	0.0006
				(4.33)	(3.89)	(1.04)
Traditional Index(1-Crisis)*				0.0010**	0.0016***	-0.0007
				(2.27)	(2.69)	(-1.58)

Table 9

This table displays partial results (marginal effects) for alternative specifications of equations (1) and (2). *Subchapter S Bank* is a dummy variable equal to one for banks organized under subchapter S corporations. *Multi-bank Holding Company* is a dummy variable equal to one for multi-bank holding companies. All models are estimated using a pooled probit model with year fixed effects and a first-stage Heckman correction. Cells display the estimated marginal probabilities; *Z*-statistics for the raw probit coefficients appear in parentheses and are based on standard errors clustered at the bank level. Data for banks with assets between $500 million and $10 billion at the start of the 1997-2012 time period. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Sample:	[1] $500M to $10B	[2] $500M to $10B	[3] $500M to $10B	[4] $500M to $10B
Traditional Index	0.0012**	0.0011**		
	(2.27)	(2.47)		
*Traditional Index*Crisis*			0.0025***	0.0024***
			(4.30)	(4.33)
Traditional Index(1-Crisis)*			0.0011**	0.0010**
			(2.20)	(2.24)
Subchapter S Bank	0.0295		0.0409	
	(0.66)		(1.07)	
Multi-bank Holding Company		-0.0017		-0.0070
		(-0.13)		(-0.50)

Table 10

This table displays partial results from estimating equations (1) and (2) using different statistical techniques. The cells contain the estimated marginal probability of bank survival with respect to the *Traditional Index* variable. *Z*-statistics for the raw coefficients appear in parentheses. All models include control variables and year fixed effects. Standard errors are clustered at the bank level in all models. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

	Equation (1)			**Equation (2)**		
	[1]	[2]	[3]	[4]	[5]	[6]
Sample:	$500M to $10B	$500M to $2B	$2B to $10B	$500M to $10B	$500M to $2B	$2B to $10B
A: Pooled probit (with Heckman correction)						
Traditional Index	0.0012**	0.0019**	-0.0002			
	(2.25)	(2.18)	(-0.48)			
*Traditional Index*Crisis*				0.0025***	0.0034***	0.0008
				(4.32)	(3.93)	(1.33)
Traditional Index(1-Crisis)*				0.0011**	0.0018***	-0.0004
				(2.19)	(2.60)	(-0.87)
B: Panel probit (with bank random effects)†						
coefficient on Traditional Index:	0.0006**	0.0007***	-0.0002			
	(2.51)	(2.66)	(-0.50)			
*Traditional Index*Crisis*				0.0011***	0.0010**	0.0005
				(3.02)	(2.46)	(0.75)
Traditional Index(1-Crisis)*				0.0006*	0.0006*	-0.0004
				(1.70)	(1.69)	(-0.70)
C: Pooled linear probability (with Heckman selection)						
coefficient on Traditional Index:	0.0008***	0.0009***	-0.0001			
	(2.87)	(2.96)	(-0.15)			
*Traditional Index*Crisis*				0.0014***	0.0014***	0.0008
				(5.03)	(4.74)	(1.51)
Traditional Index(1-Crisis)*				0.0007**	0.0009***	-0.0004
				(2.56)	(3.00)	(-0.70)
D: Panel linear probability (with bank random effects)						
coefficient on Traditional Index:	0.0008***	0.0009***	-0.0001			
	(3.04)	(3.11)	(-0.11)			
*Traditional Index*Crisis*				0.0011***	0.0011**	0.0004
				(2.85)	(2.50)	(0.86)
Traditional Index(1-Crisis)*				0.0007**	0.0008**	-0.0003
				(2.04)	(2.30)	(-0.44)

† Likelihood-ratio tests indicate that the panel probit estimations (panel B) are not statistically different from the pooled probit estimations (panel A).

Figure 1

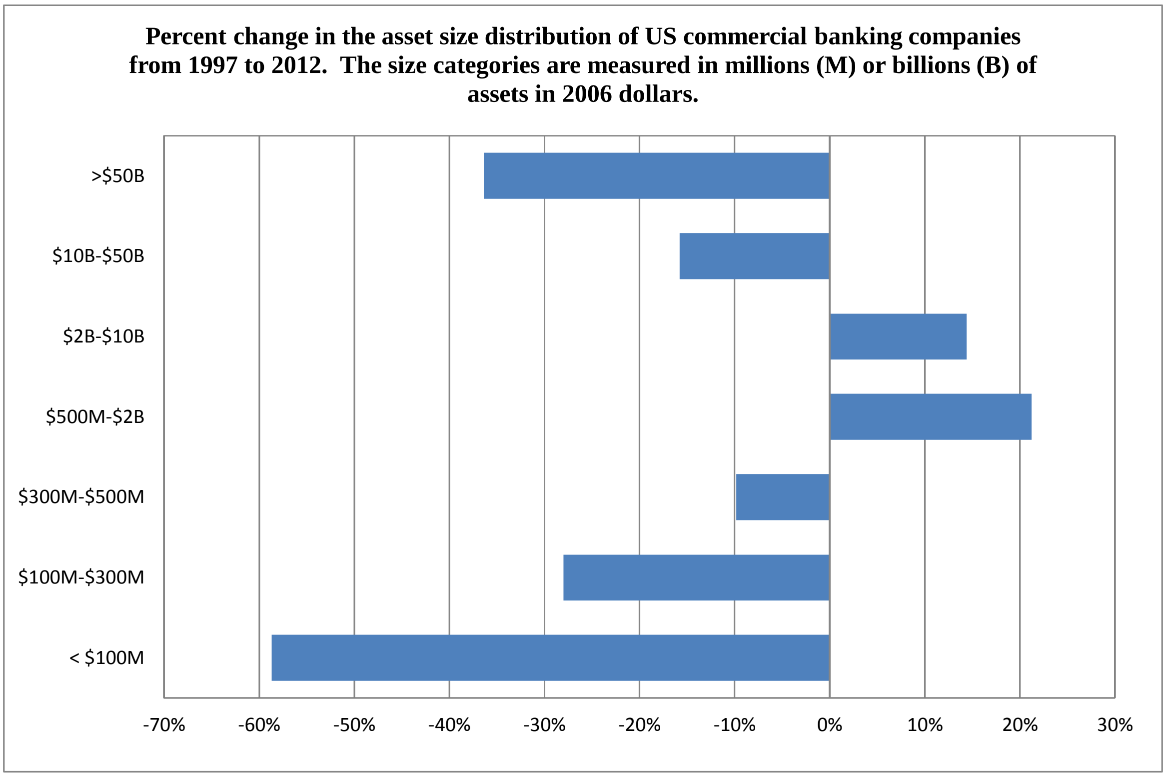


Figure 2

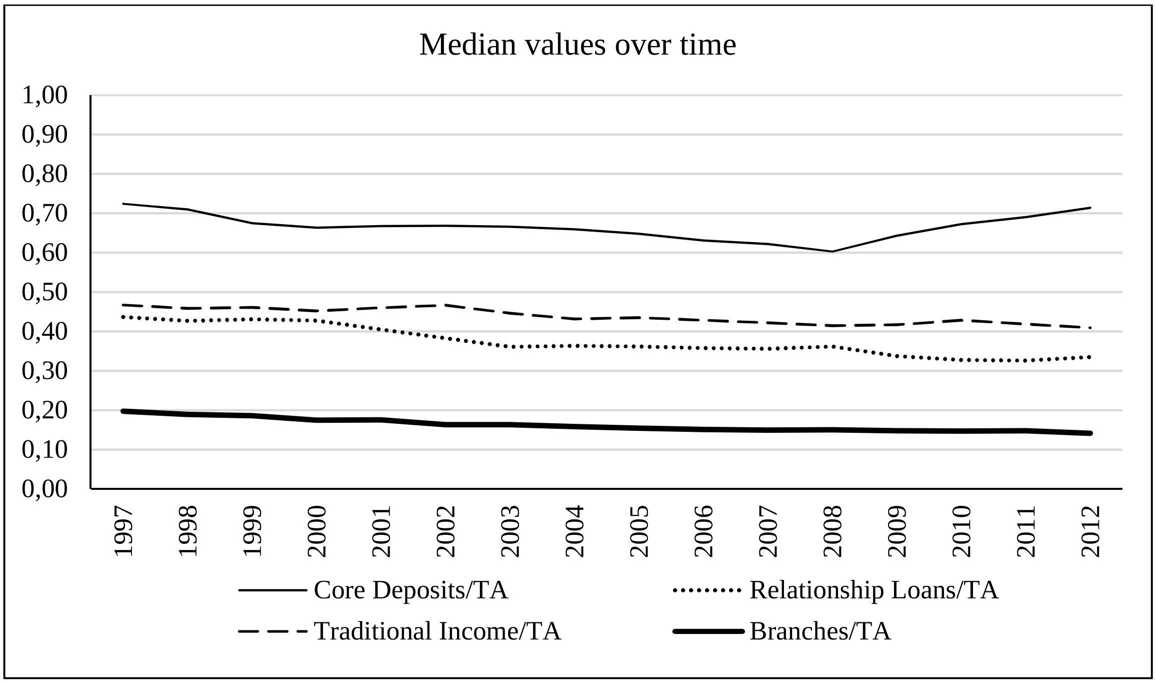


Figure 3

Probablity of survival ***from year t-1 to year t***, conditional on value of *Traditional Index*. Solid line is based on the estimated model from Table 5, column 2, evaluated at the means of the 1997-2012 panel data. Dashed lines are 99% confidence boundaries.

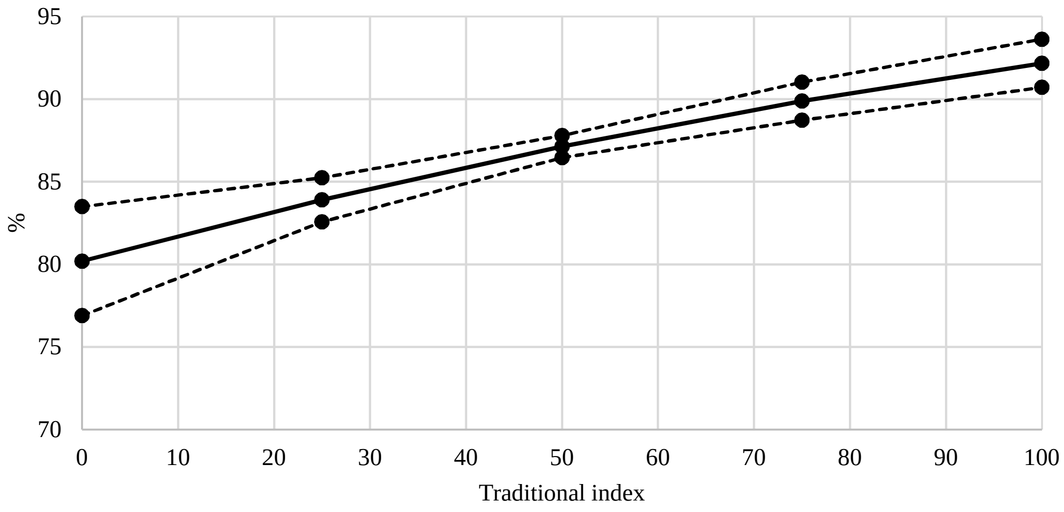


Figure 4

Probablity of survival ***from 1997 to 2012***, conditional on value of *Traditional Index*. Solid line is based on the estimated model from Table 5, column 2, evaluated at the means of the 1997-2012 panel data. Dashed lines are 99% confidence boundaries.

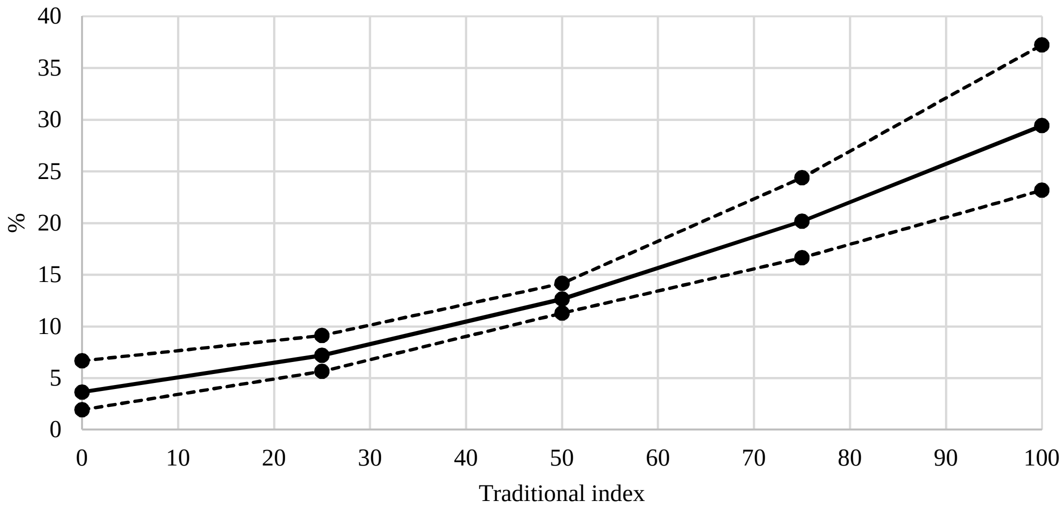
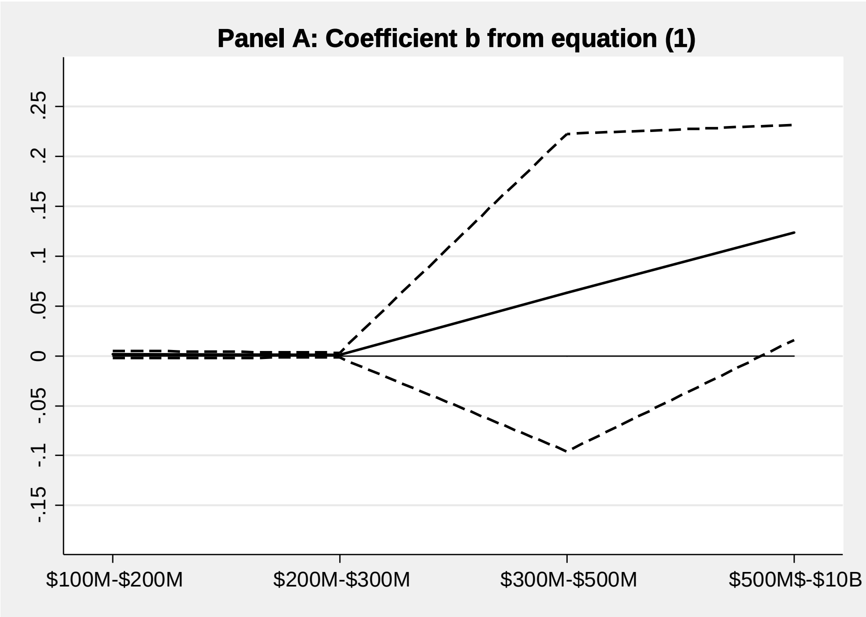
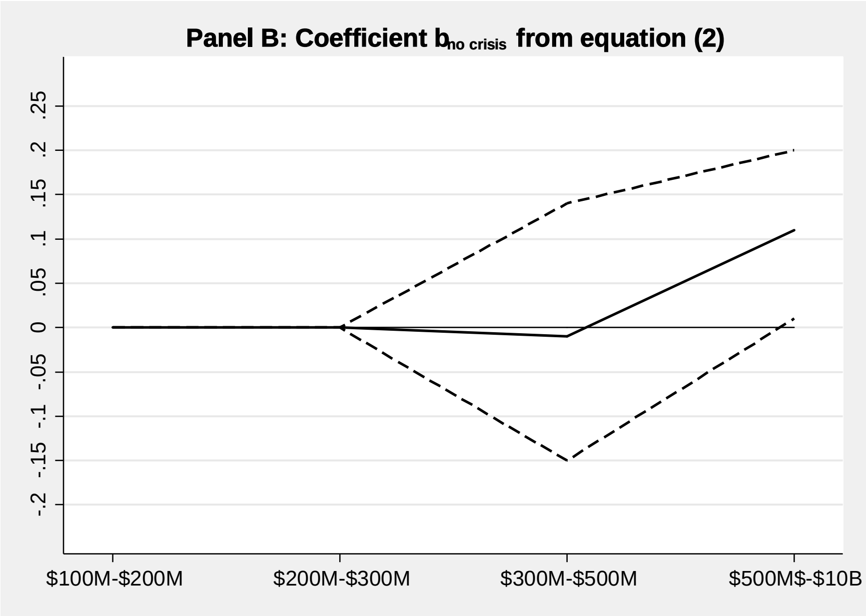
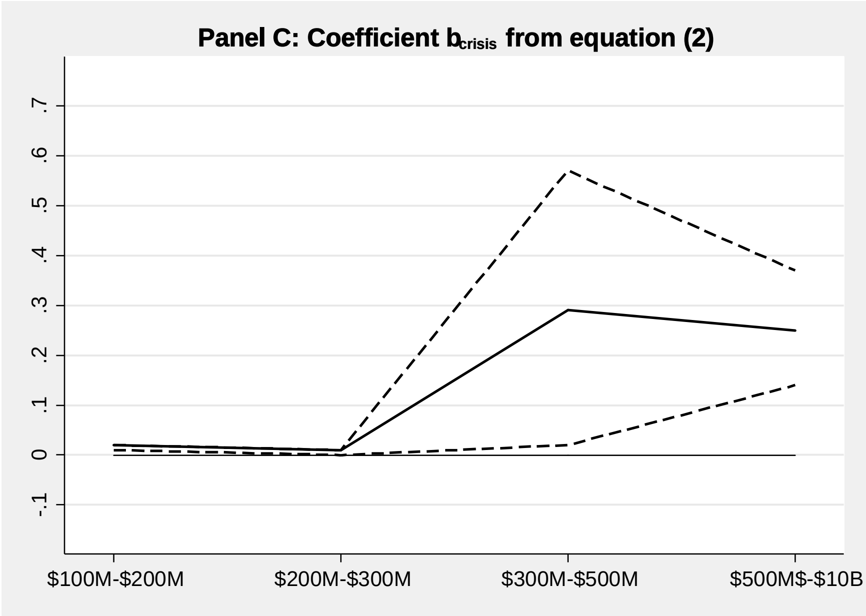


Figure 5

Point estimates and 95% confidence intervals for the coefficients *b*, b_{crisis} and $b_{no\ crisis}$ estimated for four separate subsamples of banks: Assets between \$100 and \$200 million, assets between \$200 and \$300 million, assets between \$300 and \$500 million, and assets between \$500 million and \$10 billion. Panel A shows estimates of equation (1). Panels B and C show estimates of equation (2).






Panel C: Coefficient b_{crisis} from equation (2)
.7
.6
.5
.4
.3
.2
.1
0
-.1
$100M-$200M
$200M-$300M
$300M-$500M
$500M$-$10B

Appendix Table A1

Definitions and summary statistics for all variables in Tables 2 and 3. 546 observations of banks at year-end 1997.

Name	Definition	Mean	Std. Dev.	Min	Max
Business Loans	Commercial and industrial loans (not secured by real estate), as a percentage of total assets.	9.8	7.7	0.0	49.6
Household Loans	Consumer loans, 1-4 family mortgage loans, and home equity loans, as a percentage of total assets.	34.7	16.7	0.0	99.6
Relationship Loans	*Business Loans* plus *Household Loans.*	44.5	14.2	7.1	99.6
Real Estate Loans	Commercial real estate loans, construction and development loans, and nonfarm nonresidential mortgages, as a percentage of total assets.	11.9	7.7	0.0	63.0
Total Loans	Total loans divided by total assets.	62.5	13.0	14.0	99.6
Core Deposits	Transactions deposits and small time deposits, as a percentage of total assets.	71.2	10.0	44.9	88.5
Noninterest Income	Total noninterest income as a percentage of $1,000 of assets.	10.9	16.0	0.2	262.8
Traditional Fee Income	*Noninterest Income* minus income from nontraditional financial services (e.g., investment banking, securities brokerage, loan securitization and servicing, venture capital, insurance underwriting and sales, mutual fund sales), as a percentage of $1,000 of assets.	9.2	14.2	0.1	252.5
Traditional Income	*Traditional Fee Income* plus net interest income (interest revenue minus interest expense minus provisions for loan losses), as a percentage of $1,000 of assets.	48.6	20.0	18.1	266.8
Branches	Number of branches per $1,000 of assets.	0.02	0.01	0.0	0.07
Return on Assets	Net income as a percentage of total assets.	1.1	0.4	-0.5	2.4
Noninterest Expense	Noninterest expense as a percentage of operating income (interest income plus noninterest income minus interest expense minus provisions for loan losses).	60.8	10.2	36.7	99.8
%Asset Growth, Previous 3 Years	Percentage growth in total assets between 1994 and 1997.	61.0	62.3	-14.2	254.6
Tier 1 Risk-based Capital Ratio	Tier 1 equity capital as a percentage of risk-weighted assets.	14.2	5.9	8.0	54.0
Risk-weighted Assets	Risk-weighted assets as percentage of total assets.	64.3	12.8	25.6	171.3
Nonperforming Loans	Loans 90 days past due plus nonaccrual loans, as a percentage of total assets.	0.6	0.8	0.0	11.5
Funding Gap	Total loans as a percentage of total deposits.	75.8	16.9	25.2	114.4
Unused Loan Commitments and Lines	Unused loan commitments as a percentage of total assets.	0.1	0.1	0.0	0.4
Liquid Assets	Cash, interest-bearing cash, and securities, as a percentage of total liabilities.	25.4	12.4	3.2	71.8

Appendix Table A2

Definitions and summary statistics for all variables used in the estimates in Tables 5 and 7. 546 observations of banks at year-end 1997.

Name	Definition	Mean	Std. Dev.	Min	Max
Survive	Equals one if bank survived from 1997 through 2012.	0.45	0.5	0.0	1.0
Traditional Index	An index running from 0 (a fully nontraditional bank) to 100 (a fully traditional bank). Additional details available in the text.	39.6	12.1	0.0	100.0
State GDP	State-level average annual GDP growth rate for 1997-2012, minus US average annual GDP growth rate for 1997-2012, expressed as a percentage.[1]	-0.2	1.0	-3.0	3.6
State Unemployment	State-level average annual unemployment rate for 1997-2012, minus US average annual unemployment rate for 1997-2012, expressed as a percentage.[1]	-0.1	0.9	-4.8	2.4
State Credit Quality	State-level average annual nonperforming loan ratio for 1997-2012, minus US average annual nonperforming loan ratio 1997-2012, expressed as a percentage.[1,2]	-0.7	0.5	-2.7	1.2
lnAssets	Total assets, in millions of 2006 dollars, expressed as natural log.	6.8	0.7	6.0	9.0
Risk-weighted Assets	Risk-weighted assets as percentage of total assets.	64.3	12.9	25.6	171.3
Nonperforming Loans	Loans 90 days past due plus nonaccrual loans, as percentage of total assets.	0.6	0.7	0.0	11.5
Loan Concentration	Herfindahl index of loan portfolio shares (real estate loans, commercial and industrial loans, agricultural loans, loans to depository institutions, loans to individuals, loans to foreigners).	0.6	0.2	0.3	1.0
Commercial Real Estate Loans	Nonfarm nonresidential mortgage loans as percentage of total assets.	11.9	7.7	0.0	63.0
Construction Loans	Constructions and development loans as percentage of total assets	3.0	3.0	0.0	23.0
Goodwill	Goodwill, as percentage of total assets.	0.3	0.5	0.0	3.4
Risk-based Capital	Tier 1 equity capital as a percentage of risk-weighted assets.	9.0	2.7	5.1	33.1
Funding Gap	Total loans as a percentage of total deposits.	75.8	16.9	25.2	114.4
Noninterest Expense	Noninterest expense as a percentage of operating income (interest income plus noninterest income minus interest expense minus provisions for loan losses).	60.7	11.2	16.4	133.9
Return on Assets	Net income as a percentage of total assets	1.1	0.6	-5.7	5.2
HHI	County deposit share Herfindahl index.[3]	0.2	0.1	0.0	0.7
Urban	Equals 1 if the bank is headquartered in a Metropolitan Statistical Area (MSA)	0.8	0.4	0.0	1.0

[1] When a bank operates in more than one state, we construct a multistate average, using the proportions of the bank's deposits in each state as weights.
[2] We calculate the state-level average nonperforming loan ratios using data only from banks that get at least 75% of their deposits from within the state.
[3] When a bank operates in more than one county, we construct a multicounty average, using the proportions of the bank's deposits in each county as weights.

Appendix Table A3

First-stage Heckman estimations. Probit estimation for the probability of selection into the second stage sample. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Risk-based Capital	-0.00315***
	(0.00092)
Funding Gap	0.00128***
	(0.00019)
Risk-weighted Assets	-0.00093**
	(0.00036)
Return on Assets	-0.00454*
	(0.00273)
Loan Concentration	-0.08341***
	(0.01780)
Commercial Real Estate Loans	0.00085***
	(0.00031)
Noninterest Expense	-0.00150***
	(0.00022)
Goodwill	0.01767***
	(0.00186)
ln(Population)	0.00985***
	(0.00317)
ln(Per Capita GDP)	0.12663***
	(0.02030)
Age	-0.00039***
	(0.00008)
N	79,641