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Bank Size, Lending Technologies, and Small Business Finance

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May 2008

Abstract

Under the current paradigm in small business lending research, small banks have comparative advantages in lending to the smallest, least informationally transparent firms using lending technologies based primarily on “soft” qualitative information, while large banks tend to specialize in lending to larger firms using technologies based more on “hard” quantitative information. We test this paradigm using data on U.S. small businesses, the banks that lend to these firms, the contract characteristics of their loans, and other information. To conduct the tests, our analysis begins with the identification of 10 distinct lending technologies used by the banks to make small business loans. Our results suggest that large banks do not have comparative advantages over small banks in all of the hard lending technologies and the comparative advantages of large banks in the hard technologies are not increasing in firm size. These and other findings conflict with some of the predictions of the current paradigm, and suggest that some of the most restrictive assumptions of the paradigm be relaxed.

JEL Classification Numbers: G21, G28, G34, L14

Key words: Banks, Lending Technologies, Relationship Lending, Small Business.

The views expressed do not necessarily reflect those of the Federal Reserve Board or its staff. The authors thank Bob Avery, Brian Bucks, Diana Hancock, Traci Mach, Greg Udell, John Wolken, and participants at a seminar at the Federal Reserve Board for helpful comments and suggestions and Dan Grodzicki and Phil Ostromogolsky for valuable research assistance.

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Bank Size, Lending Technologies, and Small Business Finance:

1. Introduction

The current research paradigm in small business lending emphasizes the advantages of small banks in lending to small, opaque firms, and, conversely, the advantages of large banks in lending to large, transparent firms. In this paradigm, loan officers at small banks have more flexibility than those at large banks to evaluate credit using techniques based primarily on “soft” qualitative information that is difficult to quantify and communicate by the loan officers – such as personal knowledge about the subjective circumstances of the firm, its owner, and its management. Loan officers at large banks are hypothesized to focus more on lending to larger, more transparent firms using their comparative advantages in lending technologies based primarily on “hard” quantitative information that the loan officers may credibly communicate to others in the bank – such as financial ratios calculated from certified audited financial statements, collateral values, and credit scores.

In contrast to this paradigm, however, large banks appear to be aggressively pursuing very small business credits using “hard” information-based technologies. A recent Wall Street Journal article provides some anecdotal support for this trend, showing that banking giants, such as Bank of America, are loosening their standards on small credits to small businesses by relying on “hard” information such as owners’ personal credit scores (Enrich 2007). Data from bank regulatory reports are also consistent with the finding that large banks are very active in small business lending, including loans to the smallest of these firms. The June 2006 supplement to the Call Report on small business lending shows that over 65% of the dollar value of business loans of \$1 million or less and over 68% of the value of such loans of \$100,000 or less were made by banks with over \$1 billion in assets. Our results shown below are also consistent with the fact that most small business loans are made by large banks. Based on the 1998 Survey of Small Business Finance (SSBF), we find that banks with over \$1 billion in assets make about 60% of all small business loans, similar to their market share of bank branch offices.

In this paper, we test the current paradigm in small business lending research. Our tests allow for the possibility that large banks have a comparative advantage in lending to small businesses, including the smallest, least transparent firms, using hard-information lending technologies. Specifically, we allow for the possibility that large banks use techniques such as the leasing of assets, lending based primarily on

collateral values, and small business credit scoring to lend to the smallest firms. Our test results suggest that the data often conflict with the predictions of the current paradigm, and suggest that some of the most restrictive assumptions be relaxed.

Under the current paradigm, large banks generally have a comparative advantage in using hard-information lending technologies, and small banks tend to have an advantage in soft-information technologies. In most cases, the research tends to lump the hard technologies together, and assumes that the advantage of large banks in using these technologies is increasing in the size of the borrowing firm. The grouping together of the hard technologies often originates from an assumption that hard technologies as a whole may be represented by a single technology – financial statement lending – which relies primarily on statistics in firms’ financial statements. As firms increase in size, they tend to have higher-quality financial statements, yielding an implied increasing advantage in hard technologies.

Under the current paradigm, researchers also generally assume that there is only one important soft-information technology – relationship lending – which is based primarily on information gathered over the course of a bank-borrower relationship, such as the owner’s character or reliability. Authors of this research often do not explicitly identify lending technologies, but rather examine the effects of relationship lending using only a measure of bank-borrower relationship strength, such as length or breadth. Stronger relationships are presumed to be more often associated with relationship lending and weaker relationships are presumed to be more often associated with hard technologies. As discussed below, this approach may result in significantly biased or misleading research findings.

Our empirical analysis matches data on U.S. small businesses, the banks that lend to them, the contract characteristics of these loans, and information from several other data sources to test the empirical implications of the current paradigm. The data set includes information about the loan contract, the borrower, the bank, and the bank-borrower relationship for 2460 small business loans.

Using these data, we empirically identify 10 distinct lending technologies used by the banks to make significant numbers of small business loans – financial statement lending plus seven other hard technologies, and relationship lending plus one other soft technology. This approach is more comprehensive than prior empirical studies, which usually either rely on a single measure of relationship strength or identify one or two lending technologies.

Our analysis relaxes some of the most restrictive assumptions of the current paradigm. First, we allow for the possibility that large banks may have a comparative advantage in hard technologies as a whole, but may not have advantages in all of the individual hard technologies. Second, we relax the assumption that hard technologies as a whole may be represented by financial statement lending. Third, we permit the comparative advantage of large banks in hard technologies as a whole to be increasing, decreasing, or nonmonotonic in firm size. Finally, we ease the assumption under the current paradigm that relationship lending is the only important soft-information lending technology.

Our main empirical findings are:

- 1) Large banks do not appear to have comparative advantages in all of the hard lending technologies, although they may have an advantage in hard technologies as a whole;
- 2) Financial statement lending does not appear to be representative of hard technologies as a whole;
- 3) The measured comparative advantages of large banks in hard technologies do not appear to be increasing in firm size; and
- 4) Banks may use a soft-information technology based on loan officer training and experience that was not identified in prior research in equal or greater quantities than relationship lending.

All four of these major results conflict with the predictions of the current paradigm, and suggest that some of the most restrictive assumptions of the paradigm be relaxed.

The remainder of the paper is organized as follows. Section 2 reviews the current paradigm. Section 3 shows how we identify the 10 lending technologies used by banks to lend to small businesses, and Section 4 shows how these technologies are distributed by firm size and bank size. Section 5 shows our methodology for testing the implications of the current paradigm, and Section 6 gives the empirical results from those tests. Section 7 concludes.

2. The current paradigm

The current paradigm for small business lending mainly concentrates on two categories of lending technologies, hard- and soft-information technologies. Hard technologies – also known as transactions technologies – are based principally on quantitative data that may be relatively easily processed and transmitted within a banking organization. Soft technologies, in contrast, are based mainly

on qualitative information that may not be easily processed and transmitted beyond the loan officer or other bank employee that collects it. We define a specific hard or soft technology by the principal or most critical source of information employed in the credit underwriting process, but we do not rule out that hard and soft information generated using other technologies play secondary roles.

Researchers employing the current paradigm often focus on a single soft technology, relationship lending, which is based principally on qualitative information gathered through contact over time with the small business, its owner, and local community (e.g., Petersen and Rajan 1994, Berger and Udell 1995, Degryse and van Cayseele 2000). Other soft technologies that may be based mainly on alternative sources of soft information are typically excluded from consideration and are not measured empirically.

Relationship lending is often thought to be superior to all hard technologies for lending to the smallest, least transparent firms, as these firms are generally presumed to lack sufficiently high-quality quantitative data on which to base the credit decisions. Relationship lending may also have the benefit of increasing the supply of credit to these opaque borrowers because the proprietary nature of the soft information provides the bank with market power to recoup subsidies on credits extended earlier in the relationship (e.g., Sharpe 1990, Petersen and Rajan 1995).

Hard technologies employed by commercial banks include financial statement lending, fixed-asset lending, asset-based lending, and small business credit scoring. The principal data source for financial statement lending is a set of statistics such as financial ratios generated from the firms' financial statements. For fixed-asset lending, the main data are appraised values of the real estate, motor vehicles, or equipment leased or pledged as collateral, while the key data for asset-based lending are valuations of accounts receivable and/or inventory pledged. Loans secured by these collateral types are considered hard technologies because the collateral provides the primary source of quantitative information about the risk and expected repayment of the loan. Small business credit scoring decisions are based principally on credit scores generated from the owner's personal credit history and limited financial data on the firm.

Despite the obvious differences in lending techniques and data sources for hard technologies, it is often explicitly or implicitly assumed under the current paradigm that hard technologies as a whole may be represented by the financial statement lending technology alone. Based on this assumption, the conclusion is often drawn that hard technologies are best suited for serving the largest, most transparent

small businesses that tend to have the highest quality financial statements. Thus, for most of the research in the current paradigm, as firms increase in size and transparency, banks tend to substitute from the soft technology of relationship lending to one of the hard technologies.

The assumptions employed about the technologies in the current paradigm may result in biased or misleading empirical results. The empirical research in most cases does not separately identify the individual hard-information technologies employed by the lending banks. Instead, researchers often simply use a measure of bank-borrower relationship strength, such as relationship length or breadth, as a continuous indicator of the degree to which the relationship lending technology versus a hard technology is effectively applied. This practice effectively groups the hard-information technologies together, so any measured effect of these technologies at best reflects an overall average effect across the individual lending methods, and may not accurately measure the effects of financial statement lending or any other single hard technology.

Moreover, the measured effect of hard technologies may be biased from the inadvertent inclusion of the effects of soft technologies other than relationship lending. That is, the measured effect of hard technologies may also mix in the effects of soft technologies that are associated with weak banking relationships. The exclusion of soft technologies other than relationship lending suggests that measured effects of relationship lending may not accurately reflect the effects of soft technologies as a whole and/or may give biased effects of relationship lending. These may be substantial problems if other soft technologies have effects similar to relationship lending and are used on a significant proportion of small business credits.

Nonetheless, some recent research recognizes the possibility that financial statement lending may not represent hard technologies as a whole, and that some of the other hard technologies may be particularly useful in lending to the smallest, least transparent firms (e.g., Berger and Udell 2006). To illustrate, small business credit scoring may be applied even when there is very limited information about the overall quality of the firm, as long as the firm has a good credit score based mostly on the credit history of the owner. Similarly, fixed-asset lending can be used to extend credit when the firm has high-quality fixed assets that may be leased or pledged as collateral, even if the small business is not sufficiently transparent based on other hard and soft information.

A few recent empirical studies have also progressed by identifying one or two specific lending technologies, rather than simply using a measure of relationship strength to separate relationship lending from hard technologies as a whole. For example, some studies empirically identify small business credit scoring based on survey data regarding whether, when, and how U.S. banks employ this lending technology (e.g., Frame, Srinivasan, and Woosley 2001, Berger, Frame, and Miller 2005, Berger, Espinosa-Vega, Frame, and Miller 2005, DeYoung, Glennon, and Nigro forthcoming). These studies confirm the possibility of banks using a hard technology to expand their small business lending to or improve their information sets about very small customers, depending on how the technology is implemented. Some recent studies of Japan have information on whether small businesses have certified audited financial statements, which may be an indicator that their banks use financial statement lending on the loans to these customers (e.g., Kano, Uchida, Udell, and Watanabe 2006). This research finds, for example, that the beneficial effect of relationship length is smaller for firms with audited statements, consistent with a predicted shifting of technologies from relationship lending to financial statement lending.

One study of Japan identifies the use of six lending technologies, but takes a very different approach from the one employed here. While we focus principally on contract terms and the bank-borrower relationship and assign a primary technology for each loan, Uchida, Udell, and Yamori (2006) focus principally on the borrower's perception of how much the bank relied on different information and do not assign a primary technology for each loan. In their application, a loan may be made using multiple technologies. They find no significant differences in comparative advantages for large and small banks in the different technologies in Japan, which is very different from our findings below. The reason for these different findings may be the different methodology, the application to a different country, or some combination of these.

Another important aspect of the current paradigm is the role of banks' organizational structure in determining their comparative advantages in different lending technologies. Most of the research on the U.S. and other developed nations is centered on the role of bank size, although studies of developing nations often focus on the roles of foreign and state bank ownership. Large banks are considered to have comparative advantages in hard technologies because they have economies of scale in the processing and

transmission of hard information, and may be better able to quantify and diversify the portfolio risks associated with hard information loans. Large banks may be disadvantaged in processing and transmitting soft information through the communication channels of large organizations (e.g., Stein 2002). Relationship lending may also be associated with agency problems within the financial institution because the loan officer that has direct contact with the firm, owner, and community is the main repository of soft information, giving a comparative advantage in relationship lending to small institutions with fewer layers of management (e.g., Berger and Udell 2002) or less hierarchical distance between the loan officer and the manager that approves the loans (e.g., Liberti and Mian 2006).

These comparative advantages of large and small banks – if they are consistent with the data – have important potential implications for the effects of bank size and industry consolidation on the availability of credit to the least transparent small firms that may have difficulty obtaining financing from large institutions. Some empirical research confirms the comparative advantages of large and small banks in small business lending using hard and soft information, respectively (e.g., Cole, Goldberg, and White 2004, Scott 2004, Berger, Miller, Petersen, Rajan, and Stein 2005). However, this research does not separate out the individual hard technologies or incorporate the possibility that large banks may use hard technologies other than financial statement lending to reach smallest, least transparent firms. Thus, even if large banks on average have comparative advantages in lending to larger firms using financial statement lending or other hard technologies, they may also be able to use some hard technologies – such as small business credit scoring and fixed-asset lending – to reach the smallest firms.

The assumptions about the lending technologies, bank size, and small businesses together yield the prediction under the current paradigm prediction noted above that the comparative advantages of large banks in hard technologies are increasing in firm size. Large banks are assumed to have comparative advantages in hard technologies, and these technologies are assumed to be represented by financial statement lending. As firms increase in size, the quality of their financial statements also generally increases, yielding the increasing comparative advantage of large banks. That is, under the current paradigm, as small businesses grow and their financial statements improve, their likelihood of being served by a large bank with an advantage in using financial statement lending increases, and this is

assumed to be representative of the use of the other hard technologies as well.¹

In this paper, we relax some of the most restrictive assumptions of the current paradigm. First, we allow for the possibility that large and small banks may have different comparative advantages for each of the individual hard technologies. All of the lending technologies employ some combination of both hard and soft information. Underwriting any loan requires at least some numbers about the firm, the owner, and/or the collateral (hard information), and some judgment of the loan officer based on experience and training (soft information). Thus, for some hard-information technologies, the comparative advantage for large banks in using the hard-information component may be offset by a comparative advantage for small banks in using the soft-information component. For example, commercial real estate lending is a hard-information technology which is based mainly on the appraised value of the property. However, there may also be a significant soft-information component based on knowledge of the market and local business conditions. Large banks may have only a slight comparative advantage in obtaining and processing the appraised values, whereas small banks may have a significant advantage in the soft information component, based on prior strong relationships with the borrowing firms or knowledge of similar commercial businesses in the local community, offsetting the advantage of large banks. This implies that large banks may not have comparative advantages in hard technologies with a significant soft-information component.

Second, we relax the assumption that hard technologies as a whole are well represented by financial statement lending. As noted above, some of the recent literature recognizes the possibility that some of the hard technologies other than financial statement lending may be particularly useful in lending to the smallest, least transparent firms, but this has rarely been applied in practice. In our application, we both 1) evaluate whether financial statement lending accounts for a majority of hard technology loans and 2) examine whether large banks have similar comparative advantages in other hard technologies.

Third, we allow large banks' comparative advantages in hard technologies to differ by the size of

¹ Empirical applications in the current paradigm also often force a monotonic association between borrowing firm size and bank size by relating a continuous measure of firm size to a continuous measure of bank size, although the sign of the relationship is not restricted (e.g., Haynes, Ou, and Berney 1999, Cole, Goldberg, and White 2004, Berger, Miller, Petersen, Rajan, and Stein 2005, Uchida, Udell, and Watanabe 2006).

borrower to which they are applied. The advantages in a given technology may differ by firm size because the relative importance of the hard and soft components may differ by the size of the borrowing firm. In the example of commercial real estate loans, the smallest firms may have the largest soft-information component related to information other than the appraised value of the property. Similarly, for leasing, more soft information may be appropriate for small leases to small firms (e.g., one motor vehicle) than for large leases to large firms (e.g., a fleet of motor vehicles).

Fourth, we postulate an important soft-information technology other than relationship lending, which we term, “judgment lending.” While judgment of the loan officer is important soft information for virtually any lending technology, in some cases, it may be the principal information source. Some small businesses do not have significant quality hard information available and have not established a strong banking relationship. The loan officer may still make a judgment to provide credit based on the officer’s personal experience and training, as well as any other available hard and soft information. Because this technology is based primarily on soft information that is difficult to transmit through the communication channels of large organizations, we hypothesize a comparative advantage for small banks.

3. Identification of the lending technologies

In this section, we identify 10 technologies used by banks to lend to small businesses that responded to the 1998 SSBF. We first describe the variables used in the identification process, and then explain how we combine these variables to identify the technologies.

Table 1 shows brief descriptions and summary statistics for the variables used to identify the technologies. The means and standard deviations are computed for all 2460 individual bank loans for which we are able to identify the technology and match the loan to the bank that provided the credit.² Although some firms have loans from other types of financial institutions, we confine attention to bank loans because banks are the only institutions that use almost all the major technologies, giving the best representation of the use of comparative advantages in the most technologies. Fortunately, banks are also the most popular source of loans, and at least some banks are conveniently available to virtually every

² About 13% of the bank loans are excluded because the bank could not be determined. We also exclude 5 bank loans to firms with total assets ≤ 0 and another four for which the type of collateral could not be determined.

small business.

The variables used in the identification process include several loan contract characteristics – contract type (lease versus loan), type of collateral pledged if any, and credit size (maximum of loan or line of credit amount). We also include information on the firm (firm size, leverage), the owner of the firm (personal bankruptcy/delinquency), and the relationship between the firm and the lending bank (relationship length and breadth, which are combined to measure relationship strength). Finally, we include one bank characteristic, a dummy for bank size.

We next show how we employ these variables to identify the 10 technologies. The process is depicted graphically in three steps in Figure 1. For each technology, we give the required values of the variables; describe the principal source of information used by the bank in the screening, underwriting, and monitoring of the credit; indicate whether the information used is primarily hard versus soft; and give the percent of total bank small business loans identified as using the technology. The process is quite simple because the technologies are in effect determined one at a time and eliminated from the pool. In most cases, only one or two additional variables are needed to identify the next technology, given that all of the previously-identified technologies that have been ruled out. As discussed above, we identify a technology by the principal source of information used, but we do not rule out that hard and soft information generated using other technologies plays a secondary role.

We follow several basic principles in the hierarchy in Figure 1. First, we argue that to evaluate each potential borrower, the bank will choose the lending technology that is most efficient for that firm based on the available collateral and other information that the firm brings to the table, as well as any information that the bank already has about the firm. Based on this principle, we argue that the bank will generally choose a hard-information technology over a soft-information technology if sufficient hard information is available. Soft-information techniques tend to be labor-intensive on the part of the loan officer and the information generated is difficult to communicate, so a hard-information technology with information that is less costly and easier to transmit will be chosen if possible. Following this principle, we assess the available hard information to identify the hard technologies before the soft technologies.

Next, we argue that lending based on the values of fixed assets that are leased or pledged as collateral is generally more efficient than other hard-information lending technologies if this collateral is

available. Fixed assets are long-lived assets that are not sold in the normal course of business (i.e., are “immovable”), and are uniquely identified by a serial number or a deed. These include real estate, motor vehicles, and equipment. A bank with a loan secured by fixed assets can usually collect most of its owed repayment before other creditors in the event of default or bankruptcy. Fixed-asset lending may also be particularly effective by providing a strong incentive for firms to make their payments – in many cases, the businesses may be crippled without access to their real estate, motor vehicles, or equipment. Since the bank first evaluates whether there are fixed assets to lease or pledge as collateral, we use the fixed assets pledged as collateral to identify the fixed-asset lending technologies before the other hard technologies.

Thus, in Figure 1, we first identify the loans made using the fixed-asset lending technologies in Step 1. We then identify other hard-information technologies in Step 2. We finally identify the loans made using soft-information technologies as those for which sufficient hard information does not appear to be available in Step 3.

The fixed-asset lending technologies identified in Step 1 include leasing (LEASE) as well as loans with fixed assets pledged as collateral – commercial real estate lending (CRE), residential real estate lending (RRE), motor vehicle lending (MV), and equipment lending (EQ). For convenience, we refer to leasing as a lending technology, although the asset is directly owned by the financing institution, and no loan issued. However, a lease is economically equivalent to a loan with an almost “perfect” collateral lien – the bank owns the asset and can sell it or lease it to another customer if the loan is not repaid. We consider leasing to be a fixed-asset lending technology, because the leased assets are generally fixed.

Among the fixed-asset technologies, we first identify the use of leasing (LEASE), which is simply based on whether the contract type is a lease. For leases, the principal source of information used to evaluate the credit is the valuation of the real estate, motor vehicles, or equipment that is leased. The information used in leasing is classified as primarily hard, given that the bank need do little more than determine whether the value of the asset exceeds the value of the credit outstanding. The value of fixed assets meets the definition of hard information as quantitative data that may be credibly transmitted by the loan officer. As shown in Figure 1 and Table 1, small businesses responding to the 1998 SSBF report that 4.84% of their loans are in the form of leases.

The remaining fixed-asset technologies – commercial real estate lending (CRE), residential real

estate lending (RRE), motor vehicle lending (MV), and equipment lending (EQ) – are essentially identified simultaneously. In most cases, the data set identifies just one of these types of collateral as pledged, so we classify the loan accordingly. The ordering of CRE, followed by RRE, and then MV and EQ together reflects the minority of cases in which multiple types of fixed assets are pledged. In these cases, we assume that the most valuable type of collateral describes the lending technology (with two exceptions noted below) and we assume that commercial real estate is the most valuable, followed by residential real estate, and then motor vehicles or equipment (with no ordering between them). In some cases, we cannot distinguish between MV and EQ loans because the survey question does not distinguish between the two types of collateral. In these cases, we label the technology as MV or EQ. There are two exceptions where we identify the loan as either a motor vehicle loan or an equipment loan irrespective of whether another type of collateral is pledged. If the purpose of the loan is to purchase specific motor vehicles and those motor vehicles are pledged as collateral, then we identify the lending technology as MV, whether or not another type of collateral is pledged. The same is true for equipment loans secured by the equipment being purchased (EQ).

As shown in Figure 1, we identify 15.45%, 7.64%, 14.96%, and 9.47% of all the SSBF loans as CRE, RRE, MV, and EQ loans, with an additional 6.14% identified as either MV or EQ. In total, we identify 58.50% of all bank small business loans as using the fixed-asset lending set of technologies. Note that for RRE category and for the MV or EQ category, the percentages with that particular type of collateral shown in Table 1 slightly exceed the percentages identified with the corresponding fixed-asset lending technology in Figure 1. This is because of the small number of cases in which more than one type of collateral is pledged (such as for a line of credit), and we assume that the most valuable type of collateral describes the lending technology.

We argue that when fixed assets are leased or pledged as collateral, these technologies are identified with a relatively high degree of certainty. A bank with a loan secured by fixed assets can usually collect most of its owed repayment with higher priority before other creditors in the event of default or bankruptcy and the threat of removal of fixed assets may provide a powerful incentive for borrowers to repay their loans.

Thus, we are reasonably certain of the identification of the technology used for more than half the

loans – loans using valuations of fixed assets leased or pledged as collateral. These loans also make for relatively clean tests of the comparative advantages of banks of different sizes in lending to firms of different sizes, as no information about the bank or the firm is used in the identification – just the loan contract characteristics terms (leasing contract or fixed-asset collateral pledged). Researchers have often focused on relationship lending and grouped the hard technologies together, so this may offer a first opportunity to examine the comparative advantages of large and small banks using a more detailed breakout of the fixed-asset technologies.³

The identification of the other technologies among the remaining 41.50% of loans is subject to more error. These all require somewhat arbitrary quantitative assumptions, such as limits on firm size and leverage, credit size, bank size, and the assumptions used to combine relationship length and breadth into a dummy for a strong relationship described below.

In Step 2, we next identify the remaining three hard technologies – asset-based lending (ABL), financial statement lending (FSL), and small business credit scoring (SBCS). As discussed above, we argue that once a bank has access to the associated hard information, it is more efficient to use this as the principal information source for lending, given the high costs of processing and communicating soft information about individual loans.

We first determine whether the firm has pledged accounts receivable and/or inventory as collateral, and classify the loans with this type of collateral as asset-based lending (ABL). For asset-based lending, the principal information used is the valuation of the accounts receivable and/or inventory pledged, which is hard information because it can be communicated by the loan officer once the valuation is made. As shown in Figure 1, ABL accounts for 9.02% of the loans. This is below the 15.04% of all loans that have this type of collateral shown in Table 1 because many of these loans also have fixed assets pledged as collateral, and are identified as using one of the fixed-asset lending technologies.

The remaining loans have no fixed assets or accounts receivable/inventory pledged, so this

³ An additional benefit of removing fixed-asset loans from the pool first is that the identification of the remaining technologies may be more accurate. An example of this in prior research is that some researchers focusing on relationship lending use only lines of credit, which are generally not based on fixed assets (e.g., Berger and Udell 1995).

implies that the principal basis of information is likely a source other than collateral values.⁴ We identify these remaining loans as based on financial statement lending (FSL) when the loan is to a large firm (TA > \$1 million) with low or moderate leverage (firm liabilities/total assets \leq 0.9). The label “large firm” is a measure of relative size within the classification of small businesses with up to 500 full-time employees. As shown in Table 1, 39.51% of the firms are large by this definition, and 70.33% have 90% or less of their assets financed by debt. The firm size condition is based on the assumption that only the financial statements of large firms are of sufficiently high quality to base the loan on financial ratios determined from them, i.e., make them a financial statement loan. The financial ratios and the summary statistics of these ratios used in evaluating the loans are hard information that can be transmitted by the loan officer to others in the bank. For this technology, we also require that the financial statements themselves reflect a sufficiently strong financial condition, since a very weak financial condition on the financial statements may not justify an FSL loan, necessitating the use of another technology for approval of the loan. We proxy for this by requiring that the firm have low or moderate leverage. The FSL loans total 8.94% of all bank small business loans.⁵ The relatively small percentage of financial statement loans results because most of the large firms that would otherwise qualify for this lending technology are identified as fixed-asset loans in Step 1 above.

The final hard technology is small business credit scoring (SBCS). The principal source of information in SBCS is a model-based credit score that mainly uses the owner’s personal credit history obtained from consumer credit bureaus and limited financial information on the firm and loan. The score is hard information that may be credibly transmitted by the loan officer to others in the organization. We first require that the firm size be small or medium, ruling out large firms with total assets over \$1 million, so that the owner’s personal credit is important enough relative to the firm. As shown in Table 1, 60.49% of loans are to small or medium firms. We also require that the owner be both non-bankrupt in the past

⁴ Only 10% of the remaining loans have other forms of collateral, including business securities or deposits and personal assets other than real estate, and these forms of collateral tend to be of far lesser value than fixed assets or account receivable/inventory.

⁵ We also try requiring the use of financial records in responding to the survey as a condition for financial statement lending, as use of records may be an indicator of the importance of the financial statements. However, this additional condition has no effect, as all of the loans that we identify as financial statement loans also use records.

(not declared personal bankruptcy) and not been personally delinquent at least 60 days in the prior three years. Table 1 shows that 99.31% of owners have not declared bankruptcy and 90.49% have avoided recent personal delinquency. In addition, we impose the requirement that the credit be \leq \$100,000, given that scoring banks often impose this limit on use of this technology (Frame, Srinivasan, and Woosley 2001). As shown, 61.30% of the loans are small by this definition. Finally, we limit the use of this technology to large banks, given that this technology is not believed to have diffused to many small banks as of 1998. As shown, 59.84% of loans are made by large banks. With these conditions, we identify a total of 11.83% of the loans as processed using SBCS, which is indicated in the last technology of Step 2 in Figure 1. In our regression analysis, discussed below, we try dropping the loans identified as made using SBCS from the group of hard lending technologies as a robustness check. This is because our assumption that only large banks use SBCS effectively “engineers in” a perfect comparative advantage for large banks in this lending technology.

The remaining loans in Figure 1 are based primarily on soft information. We argue that at this point, we have eliminated having enough hard information on which to base the loan from valuations of fixed assets or accounts receivable/inventory pledged as collateral or from strong, informative financial statements or model-based credit scores. Recall that we identify technologies employed only for bank loans that are outstanding, and so we exclude from consideration cases in which a loan application was processed using one of the technologies, but credit was denied.

The first soft technology identified is relationship lending (RELATE). The requirement for relationship lending is that a firm has a strong relationship with its lender. We examine the length and breadth of the relationship between the firm and the bank extending the loan, and combine these in different ways to measure whether the relationship is “strong.” Most measures of relationship strength in the literature focus on length, as longer relationships allow more time for the lending bank to garner proprietary soft information about the firm (e.g., Petersen and Rajan 1994, Berger and Udell 1995). Some strength measures include breadth in the form of a checking account that the bank gain information from monitoring the firm’s cash flows (e.g., Mester, Nakamura, and Renault 2007). Others focus on breadth in the form of lender exclusivity, as accumulation of all of a firm’s credits in a single bank maximizes the information advantage of that bank (e.g. Rajan 1992, Berger, Klapper, and Udell 2001, Berger, Miller,

Petersen, Rajan, and Stein 2005).

As shown in Table 1, 41.99% of the loans are to firms with short relationships with their lending bank (≤ 5 years), 25.93% are to firms with medium relationships (> 5 years, ≤ 10 years), and 32.07% are to firms with long relationships (> 10 years). With respect to relationship breadth, 79.23% of the firms also have a checking account at the bank, and for 39.51%, the bank is the firm's exclusive lender, providing all of the firm's loans (which also rules out loans from nonbank financial institutions).

For a strong relationship, we require that the firm's relationship with the bank have both length and breadth, with some trade-off between these two dimensions. If the relationship is long – over 10 years – we require at least one dimension of breadth – the bank have either a checking account of the firm and/or serve as the firm's exclusive lender. If the relationship length is medium – over 5 years and up to 10 years – we require that the bank have both a checking account of the firm and be the exclusive lender. As shown in Table 1, 29.59% of the loans are to firms with strong relationships with their lending banks by our definition.

The principal source of information in relationship lending is the loan officer processing of information through contact over time with the firm, its owner, and others in the local community that may be suppliers or customers, and so forth. The information is primarily soft because such information cannot be easily reduced to hard numbers that can be easily communicated by the loan officer, such as values of assets, financial ratios, or credit scores. We identify 4.07% of bank small business loans as using relationship lending. This is much smaller than the 29.59% of the loans associated with strong relationships, because most of the firms with strong relationships are identified as being served using one of the hard-information lending technologies.

Our final technology is judgment lending (JUDGE), a residual category inferred in Figure 1 from an accumulation of no's to all the prior questions. These firms do not have sufficient hard information on which to base their credit and they have not established a strong relationship to generate soft information, so their loans likely require a high degree of judgment on the part of the loan officer. The officer makes a judgment based on whatever limited hard and soft information is available about the firm, plus the officer's training and personal experience with regard to the type of business, location, local demand for the product, and so forth. The soft information may include information gathered from a relationship with

the firm, but if so, the relationship strength does not rise to the level of “strong” as we define it here. Importantly, the training and experience of the loan officer are also primarily soft information, as they generally cannot be reduced to credible hard numbers that may be easily communicated. Overall, the information used in judgment lending is primarily soft and difficult to communicate by the loan officer, stemming mostly from a combination of training and experience with other borrowers as well as soft information gathered from the firm. As shown in Figure 1, we classify 7.64% of loans as judgment loans.

As shown at the bottom of the figure, we identify 88.29% of all bank loans to small businesses as using the 8 hard technologies – mostly the 5 fixed-asset technologies. The remaining 11.71% use the two soft technologies, which are mostly identified as judgment loans.

4. The lending technologies by firm size and bank size

In this section, we use the identification of the lending technologies in the prior section to take a first look at the distribution of these technologies by firm size and bank size. We follow the logical flow of our more detailed econometric analysis below in which firm size may be important in determining the best technology to serve the firm. Banks of different sizes are hypothesized to have comparative advantages in different technologies, and we also allow for the possibility that these comparative advantages may differ by firm size. Thus, for example, small banks may have comparative advantages in soft technologies, but these advantages may be neutralized for the largest small businesses that are generally the most transparent, and so may more easily be served by large banks using hard technologies.

In Table 2, we show the frequency distribution conditional on firm size of each of the 10 technologies shown in Figure 1. We include three firm size classes – small, medium, and large – with $TA \leq \$100K$, $\$100K < TA \leq \$1M$, and $\$1M < TA$, respectively (K, M indicates thousands, millions). As shown at the bottom of Table 2, there are 2460 loans in the sample, of which 479 are made to small firms (19.47%), 972 to medium firms (39.51%), and 1009 to large firms (41.02%). As a reminder, these labels are measures of relative size within the standard classification of U.S. small businesses – all of the firms meet the SBA guidelines of small businesses with up to 500 full-time employees.

The last two columns of Table 2 show the technology percentages for all firms by weighted frequency and by dollar amount. In column (5), the frequencies for each technology are weighted using the stratified sampling weights provided in the SSBF. These are generally similar to the unweighted

totals and are not pursued further here in the interest of brevity and to keep our focus on firm size and technology.⁶ In column (6), which shows the percentages by dollar amount, the average loan sizes differ significantly across the different technologies. Commercial real estate loans and asset-based loans tend to be large in dollar value whereas credit-scored loans tend to be small in dollar value (by assumption).

The small firms using our definition of $TA \leq \$100K$ are typically the youngest and least transparent but may be served using hard technologies such as small business credit scoring that relies on the owner's personal credit history and other technologies based primarily on personal assets pledged by the owner, such as residential real estate lending. The medium firms start getting beyond the range where the owner's personal history or assets matter, but may be old enough to have established strong relationships that are needed for relationship lending. The large firms may be best served by technologies that require significant scale – such as asset-based lending – or transparency – such as financial statement lending – and may not be easily served using soft technologies.

The numbers in Table 2 show the percent of loans to each firm size class made using each technology. For example, the first number in column (1) indicates that 4.59% of loans to small firms are made using the leasing technology. Column (4) replicates the full-sample percentages shown earlier in Figure 1. Under the null hypothesis that firm size is irrelevant for the use of a particular technology, we would expect the numbers in columns (1), (2), and (3) to be roughly equal to the column (4) entry.

There are several notable differences among the fixed-asset technologies in Table 2. The use of residential real estate lending declines dramatically with firm size, consistent with the expectation that the personal property of the owner becomes less relevant for larger firms. The use of commercial real estate lending increases with firm size, perhaps because larger firms are more likely to own such property. Equipment lending also rises with firm size, which may be related to the generally higher risk of smaller firms – equipment is likely the most difficult of the fixed assets for the bank to liquidate in the event of default.

Some of the differences in the loans made by firm size class to the other hard technologies are

⁶ The weights are based on ethnicity, geographic location, and firm size. Large, non-minority firms (50 or more employees) are oversampled. Therefore, using the weights reduces the proportion of loans to large firms, which explains the decline in the financial statement lending percentage.

“engineered in” by our assumptions used in identifying the technologies. Financial statement lending (FSL) is explicitly restricted to the large firms with TA > \$1 million and small business credit scoring is explicitly restricted to the medium and small firms. The finding that small business credit scoring (SBCS) is much more often used for the small firms than the medium firms is likely due in large part to the restriction that credit size \leq \$100,000.

Finally, we turn to the two soft technologies – relationship lending (RELATE) and judgment lending (JUDGE). It is not surprising that these technologies are seldom used for the large firms that more often have sufficient data for one of the hard technologies. What may be surprising is that both of these technologies are close to equally used on loans made to small and medium firms. It might be expected that relationship lending would be used much more often for medium firms that that have had the time and growth to establish strong relationships, while small firms would have to rely much more heavily on the judgment of loan officers because of their greater opacity.

In Table 3, we show the frequency distributions of loans made using each of the technologies conditional on bank size. We specify two bank sizes using gross total assets (GTA) – small banks with $GTA \leq$ \$1B, and large banks with $GTA >$ \$1B (B indicates billions). The small-bank size corresponds with a common empirical definition of a community bank (e.g., DeYoung, Hunter, and Udell 2004). As shown at the bottom of the table, of the total of sample 2460 loans in the sample, small banks make 988 or 40.16% of the total, and large banks make 1472 or 59.84%.

Columns (1), (2), and (3) of Table 3 show the percentages of loans made by small banks, large banks, and all banks, respectively, using the corresponding technology. These columns are analogous to columns (1) – (4) in Table 2, except that we condition on bank size rather than firm size. Columns (4), (5), and (6) show for each technology separately the percentages of the loans made using that technology by small banks, large banks, and all banks, respectively. Thus, the numbers in columns (4) – (6) in the first row indicate that of all leases, 16.81% are made by small banks and 83.19% are made by large banks, although columns (1) – (3) indicate that leasing is a relatively small component of the small business portfolio of both sizes of banks.

We focus our attention on the columns (4) – (6), which are closer to the concept of comparative advantage. Under the null hypothesis that neither large nor small banks have a comparative advantage in

the use of a particular technology, we would expect the numbers in these columns to be roughly proportional to the proportion of branches of large and small banks in the firms' local markets. The argument here is that local market branch shares of large and small banks approximates their convenience – in the absence of any comparative advantage, firms served using the technology would simply borrow from the most convenient bank. The local market share of large banks was shown to be a powerful predictor of lending bank size in prior research (e.g., Berger, Rosen, and Udell 2007). For our simple comparisons here, we note that the average local branch share for large banks in the entire national sample is 58.74%, close to the large bank share of all small business loans of 59.84%. Thus, a large-bank percentage significantly above about 59% might suggest a comparative advantage for large banks, while a large-bank percentage significantly below this figure may suggest a comparative advantage for small banks.

Based on this criterion, the data in Table 3 suggest several significant comparative advantages by size and also some surprises where the expected comparative advantages do not appear. First, among the fixed-asset technologies, the data show little in the way of significant comparative advantages for large banks except for the technology of leasing. This is contrary to the conventional wisdom that large banks have strong advantages in hard technologies. As discussed above, small banks may use their comparative advantages in the soft-information component of these loans to offset any comparative disadvantage they may have in the hard-information component. Nonetheless, large banks appear to have a strong comparative advantage in leasing with an 83.19% share, perhaps because the almost “perfect” collateral lien against the assets means that the bank has to rely very little on any secondary sources of soft information. Large banks appear to have comparative advantages in the remaining three hard technologies – asset-based lending (ABL), financial statement lending (FSL), and small business credit scoring (SBCS) – although a perfect comparative advantage is simply assumed for small business credit scoring based on prior knowledge of this technology discussed earlier.

For the two soft technologies – relationship lending (RELATE) and judgment lending (JUDGE) – the data clearly suggest comparative advantages for small banks. Small banks have shares of 75.00% and 65.43%, respectively for these technologies, well above the small bank branch and total loan shares of about 41% for these banks. This finding is consistent with expectations. However, it may be biased by

the large-bank restriction in our small business credit scoring identification. We return to this issue in our empirical methodology.

In Table 4, we show the frequency distributions of loans by bank size conditional on both firm size and lending technology. The “All Technologies” line at the bottom of the table shows a nonmonotonic relationship between firm size and bank size – large banks make 60.75% of the loans to small firms, 53.50% of the loans to medium firms, and 65.51% of the loans to large firms. This is consistent with our arguments earlier that the small firms with $TA \leq \$100K$ may often be served using hard technologies based on the owner’s personal credit history and assets pledged as collateral, allowing large banks to make many of these loans.

The rows in Table 4 show for each of the three firm sizes and for each technology, percentages of the loans made by small banks and large banks. Thus, the numbers in columns (1) and (2) in the first row indicate that of all leases to small firms, 36.36% are made by small banks and 63.64% are made by large banks. This table extends the analysis begun in the last table on comparative advantages by giving a preliminary look at whether the comparative advantages of large and small banks in different technologies may differ by whether the loan is to a small, medium, or large firm. As a caveat for viewing this table, some of the percentages are based on a relatively small number of observations – fewer than 30 in several cases.

Looking first at the fixed-asset technologies, the data suggest that in most cases, the small-bank percentage is higher for the small and medium firms than it is for the large firms. This is consistent with the hypothesis that fixed-asset loans to small and medium firms have a greater soft-information component, where small banks tend to have an advantage. For asset-based lending, the results in Table 4 suggest that the comparative advantage of large banks is the greatest for large firms. For the other two hard technologies, Table 4 offers no new information. Large banks make all small business credit scoring loans by assumption, and all of the financial statement loans are to large firms, giving the same percentages for large and small banks as in Table 3. For the two soft technologies, small banks appear to maintain a clear comparative advantage for loans to small and medium firms, but this is essentially neutralized for large firms. It seems likely that the loans to the large firms have a greater hard-information component than the small and medium firm soft-information loans, which may reduce much

of the advantage of small banks in using these technologies.

5. Methodology

Our empirical model is designed to test the empirical predictions of the current paradigm regarding whether large versus small banks have comparative advantages in the different technologies, and how these advantages differ by firm size. In this section, we briefly describe the general model used in our empirical tests and how we change the specification to test different hypotheses when different subsets of the 10 identified lending technologies are included. We model the probability that a given bank loan is made by a large bank as a function of firm size, lending technology, interactions of firm size and technology, and control variables for competitive conditions in the banking market. We interpret a significantly higher probability of a loan being made by a large bank, conditional on competitive conditions, as evidence of a comparative advantage for large banks. The general specification is a logit equation of the form:

$$(1) \quad \ln [P(\text{loan is from a large bank}) / (1 - P(\text{loan is from a large bank}))] \\ = f(\text{firm size, lending technology, firm size} \cdot \text{lending technology, large bank} \\ \text{branch market share, bank market concentration, MSA dummy})$$

where $P(\bullet)$ indicates probability, “loan is from a large bank” is a dummy variable that is one if the loan is made by a large bank and zero if it is made by a small bank.⁷

The key exogenous variables are dummies for firm size class, lending technology employed, and their interactions, denoted by firm size \cdot lending technology. These dummies allow for tests of whether large or small banks have net comparative advantages in lending to different firm sizes, and in using the different technologies. The interaction terms are particularly important here because many of the different empirical predictions of the current paradigm concern how the comparative advantages in the lending technologies vary with firm size class.

The remaining variables in equation (1) control for local market competitive conditions. Consistent with prior research and anti-trust guidelines, we define the firm’s local banking market as the

⁷ In some cases, multiple bank loans to the same firm are included and may be made using different lending technologies.

Metropolitan Statistical Area (MSA) or non-MSA rural county in which the small business is located.⁸ The market conditions specified are the large bank market share of branches, the Herfindahl concentration index of market bank deposits, and an MSA indicator dummy. The large bank branch share accounts for the relative convenience of large and small banks. As discussed above, under the null hypothesis that neither large nor small banks have comparative advantages in the different technologies, firms may generally choose an institution based on convenience, so it is important to control for the large bank market share. The Herfindahl index is the most standard measure of market power used in bank research and anti-trust analysis, and the MSA dummy proxies for the generally greater degree of competition in metropolitan markets.

We specify three different sets of technologies in separate regressions – 1) the hard versus soft technologies; 2) the 5 fixed-asset technologies; and 3) the two soft technologies. The hard versus soft technologies specification allows us to test the two predictions of the current paradigm that large banks have comparative advantages in using hard technologies and these advantages are increasing in firm size. This is opposed to the more general predictions when some of the restrictive assumptions are relaxed, under which large banks may use different hard technologies to their advantages in serving both the largest and smallest firms. We use two different groupings of hard information, one including small business credit scoring and one excluding this technology. This is due to the fact that we “engineer in” a perfect comparative advantage for large banks in using this technology in the identification procedure.

The specification using the 5 fixed-asset technologies allows us to test the prediction of the current paradigm that large banks have comparative advantages in all of these hard technologies that are increasing in firm size versus our hypothesis above that large banks may have the most comparative advantage in leasing, while small banks may have more of an advantage in other fixed-asset lending technologies, such as commercial real estate lending, particularly to small and medium firms.

Finally, the tests using the two soft technologies allows for a first test of whether the comparative advantage of small banks in relationship lending to all size classes assumed under the current paradigm applies, and whether any such advantage may also apply to the newly identified soft technology,

⁸ In some cases, we use New England County Metropolitan Areas (NECMAs), but for convenience, we simply use the term MSA to cover both MSAs and NECMAs.

judgment lending. These tests may also suggest the extent of any bias in current studies that effectively group judgment lending with hard technologies when dividing the data only on the basis of relationship strength.

6. Empirical results

Table 5 shows summary statistics for the variables used in the four specifications of the regressions. Column (1) shows the data for the full-sample hard versus soft technology specification. The number of observations is slightly reduced from the original 2460 because the firm's market location could not be determined for 26 loans, leading to missing market characteristics. Column (2) shows the data for the hard versus soft technology specification with the data on the loans identified as using SBCS excluded. As noted, we run the hard versus soft specification without these loans because of the perfect comparative advantage for large banks that is assumed in identifying these credits as using SBCS. Column (3) gives the statistics for loans using the 5 fixed-asset technologies (the "MV or EQ" category is excluded). The number of observations is 1269, slightly more than half of the full sample. Finally, column (4) displays the numbers for the specification using the two soft technologies, in which the sample size falls dramatically to 287 loans.

As shown in Table 5, the mean of the dependent variable, the large bank dummy, is reasonably close for the full sample, the full sample without SBCS, and the fixed-asset lending sample – 59.3%, 54.3%, and 55.1%, respectively. Turning to firm size, the full sample and fixed-asset lending sample have similar proportions of small, medium, and large firms – slightly below 20% of loans to small firms ($TA \leq \$100,000$), and about 40% each to medium firms ($TA > \$100,000$ and $\leq \$1$ million), and large firms ($TA > \$1$ million). However, for the soft technologies, the small- and medium- firm percentages rise to 28.9% and 60.0%, respectively, and the large firm percentage drops to 11.1%, consistent with expectations that soft technologies are seldom appropriate for large firms. The means for each of the technology variables are essentially re-scaled values of those shown in Figure 1 above (except for the missing observations), so that the proportions all add to 1.00. The market characteristics, taken from the 1997 Summary of Deposits data, are similar across all the samples. Large banks have branch market shares between 50% and 60%, the Herfindahl concentration index averages about 0.20, and about 70% of the firms are in metropolitan competitive environments.

In all regressions, the small-firm dummy is excluded as the base case. The excluded lending technology dummy differs across the regression specifications. In the hard-soft regressions, the soft dummy is excluded; in the fixed-asset technologies regressions, the leasing dummy is excluded; and in the soft technology regressions, the judgment-lending dummy is excluded. In all cases, the interaction term between the small-firm dummy and the excluded technology dummy is also excluded as part of the base case.

Tables 6 – 9 show the regression results. In each table, we show four versions of the specification – one with firm size dummies only, one with technology dummies only, one with both sets of dummies, and one complete specification with all the dummies and the interaction terms. All estimations include the control variables for banking market characteristics. For the complete specifications, we also show the predicted probabilities for each firm size-technology combination, as explained below.

We first turn to Table 6 to analyze the full-sample hard versus soft technologies specification. Column (1) of Table 6 Panel A shows the logit regression with firm size and control variables only. This version of the model is the most similar to prior empirical research, which focuses on the effects of firm size without identifying or separating out the effects of the different technologies. One additional difference here is that we include three size classes and allow for a nonmonotonic relationship between firm size and bank size, rather than using continuous measures of firm size and bank size that force a monotonic relationship. Our goal is to allow for the possibility that large banks may use some of the hard technologies – such as small business credit scoring – to reach the opaque small firms in particular.

The null hypothesis in column (1) is that neither large nor small banks have a comparative advantage in lending to firms in a particular size class, so the coefficients on the medium and large firm dummies would both be zero – i.e., no difference from the excluded small firm dummy. Under the null, a firm would generally borrow from the most convenient local bank – independent of bank size – so the probability of borrowing from a large bank would be roughly proportional to the large bank market share in the firm’s local market. Thus, under the null, the coefficients on firm size would be zero, but the

coefficient on large bank branch market share would be positive.⁹

Under the conventional paradigm employed in much of the current small business finance literature, the coefficients on the firm size class dummies are expected to be positive and increasing. Larger firms tend to be more informationally transparent, and therefore better served by large banks with comparative advantages in hard technologies.¹⁰ When some of the most restrictive assumptions of the paradigm are relaxed, the comparative advantage of large banks in hard technologies may differ across firm sizes in various ways. The relationship between firm size and bank size may be increasing, decreasing, or nonmonotonic, depending on the sizes of firms for which large banks may best use their advantages in the different technologies.

The results in column (1) show a nonmonotonic effect of firm size on the probability of borrowing from a large bank, conditional on the control variables. The negative, significant coefficient on the medium firm dummy and the statistically insignificant coefficient on the large bank dummy suggests that, all else held equal, small firms and large firms are more likely to borrow from large banks and medium firms are more likely to borrow from small banks. These findings are not consistent with the current paradigm, but are consistent with some of the relaxations of the assumptions discussed above, under which the comparative advantages of large banks may apply more to large and small firms than to medium firms. Importantly, the large banks may use different combinations of hard and soft technologies to serve the different firm sizes, which are not broken out in column (1).

Column (2) shows the regression with the dummy for hard technologies and control variables only. The null hypothesis is that neither large nor small banks have comparative advantages in these technologies, yielding a zero coefficient on the Hard variable. Under the current paradigm, a positive coefficient is expected, as large banks are hypothesized to have comparative advantages in hard technologies. The positive, statistically significant coefficient is consistent with the paradigm and reflects an average effect of technology type across the firm size classes, given that the size classes are excluded

⁹ The large bank branch market share variable plays a similar role here to the log of median bank size in the market in the model of the relationship between bank size and firm size in Berger, Miller, Petersen, Rajan, and Stein (2005) – controlling for the local availability of large versus small banks.

¹⁰ This monotonically increasing effect may also be accentuated by legal lending limits or problems of diversification of small banks in lending to large firms, giving an additional advantage to large banks in lending to larger firms that is unrelated to the lending technologies.

from this specification.

Column (3) shows the regression with both firm size and technology, but without the interactions. The null and alternative hypotheses are essentially the same and the coefficients are very similar. The findings again suggest that large banks have comparative advantages in hard technologies, and these advantages may apply more to large and small firms than to medium firms, but the model remains incomplete without the firm size-technology type interactions.

Column (4) shows the complete specification with firm size, technology, and the interactions. Under the null hypothesis, large banks have no comparative advantage in lending to firms in any size class, and no comparative advantages in hard technologies, so all the coefficients of interest would be zero. Under the current paradigm, large banks have comparative advantages in hard technologies that apply with increasing magnitude as firm size increases. When we relax some of the assumptions of the paradigm, the large banks may be expected to have comparative advantages in the hard technologies, but the magnitude may vary in any pattern with firm size.

The results in column (4) suggest that the comparative advantage of large banks in using hard technologies is decreasing in firm size – as firms become larger, the effect of the Hard variable declines. That is, the effect is found to be strongest for the small firms as loans made to small firms using a hard technology are much more likely to be from large banks than loans using one of the soft technologies. As firm size increases, the effect of technology type on the probability of a large bank declines. To see this, we focus on the effect of the Hard variable for each of the size classes. For small firms, the effect of hard technologies is simply the Hard coefficient of 2.073. For medium firms, the effect equals the coefficient of 2.073 plus the interaction term Medium Firm \cdot Hard of -0.753 or $(2.073 + (-0.753)) = 1.320$. For large firms, the interaction effect is -1.927, yielding a much smaller effect of hard technologies of $(2.073 + (-1.927)) = 0.146$.

Finally, we turn to the control variables in Panel A of Table 6 for banking market conditions. The coefficient on large bank branch market share is positive and statistically significant, consistent with the convenience argument. Firms are more likely to borrow from a large bank if the branch offices of large banks are more convenient than those of small banks, and large bank branch market share is a proxy for this relative convenience. The coefficient on the Herfindahl index, the measure of local market banking

concentration, is not significant. The MSA dummy is positive and significant, suggesting that firms in metropolitan markets are more likely to borrow from large banks. These control variable results are essentially replicated in the other tables, except that MSA is often not statistically significant. In the interest of brevity, the control variables are not discussed further.

Panel B of Table 6 converts the effects from the nonlinear logit model into predicted probabilities. That is, we illustrate the effects of firm size and technology on the probability that a firm's loan will be from a large bank using predicted values from the complete specification in column (4) of Panel A, where we assign the control variables to their means in all cases. The first row of Panel B shows that for small firms, the predicted probability of the loan being made by a large bank increases from 24.7% to 72.3% – a statistically significant rise of 47.6% – as the lending shifts from a soft technology to a hard technology. The second row shows that for medium firms, the predicted probability of a large bank increases from 28.3% to 59.6% – a statistically significant rise of 31.3% – when technology shifts from soft to hard. For large firms, the rise is only 3.4%, from 62.0% to 65.4%, and this difference for large banks is not statistically significant. Thus, for small firms, the use of Hard raises the probability of a large bank the most, followed by medium firms. For large firms, there is relatively little predictive effect of technology – these firms have a fairly high probability of borrowing from a large bank whether their loan is made using a soft or hard technology. We also show an F-test of the null hypothesis that the effect of hard versus soft technologies is the same across all three size classes. This amounts to a test that the two interaction terms between firm size and the Hard with SBCS variable in column (4) of Panel A equal zero. As shown, we can reject the null hypothesis – the effect of technology type does appear to differ significantly by firm size.

Table 7 analyzes the comparative advantages in hard versus soft technologies with small business credit scoring (SBCS) loans dropped from the regressions. The benefit of this robustness check is that it avoids our assumption in identifying SBCS loans that only large banks use this technology, which effectively “engineers in” a perfect comparative advantage for large banks in this lending technology. The drawback is that it excludes one of the important hard technologies that large banks may use to lend

to opaque small firms.¹¹ We focus attention on the full specification shown in column (4) of Panel A and on the tests of predicted probabilities shown in Panel B, and compare the findings to those in Table 6, which includes SBCS as part of the hard technologies category. The results shown in Table 7 are qualitatively similar to those in Table 6 with one exception. When SBCS is removed, the advantage of large banks in serving the small firms is somewhat reduced and is no longer greater than the advantage of large banks in serving medium firms. This difference is not surprising, given our finding above that SBCS is primarily used for small firms. Our main findings from Table 6 that large banks have comparative advantages in using hard technologies to serve small and medium firms remain intact, whether or not SBCS is included. Again, the results are not consistent with the prediction of the current paradigm that large banks have comparative advantages in hard technologies that are increasing in firm size.

We next turn to Table 8, which shows the results of testing the 5 fixed-asset technologies. As noted earlier, these technologies are identified with the greatest certainty (we exclude the “MV or EQ” loans from the regressions). These also make for relatively clean tests of the comparative advantages of large versus small banks in lending to firms of different sizes, since no information about the bank or the firm is used in the identification. We exclude the LEASE dummy as the part of the base case and conduct most of our tests on the comparative advantage differences of large and small banks for the four collateral-based fixed-asset technologies versus leasing. As discussed above, LEASE appears to be the only fixed-asset technology with a strong comparative advantage for large banks, perhaps because of the almost “perfect” collateral lien against the leased assets makes it the purest hard-information technology with the least requirement for secondary sources of soft information for which small banks may have the advantage.

The results in Panel A, column (1) of Table 8 (firm size only) show a similar nonmonotonic effect of firm size to that found in Table 6, which is not surprising, given that the subsample of loans in Table 8 is slightly more than half of the full sample in Table 6. Column (2) (technologies only) confirms

¹¹ Note that dropping SBCS loans does not completely eliminate the effect of our assumption that only large banks use the SBCS technology. This assumption also affects the identification of the soft technologies, which follow SBCS in our identification process.

expectations of a comparative advantage for large banks in leasing versus all of the other fixed-asset technologies. Column (3) (firm size and technology, no interactions) shows similar results to columns (1) and (2). Column (4) (complete specification including interactions) reveals some interesting differences by size class. The coefficients on the technologies without interactions are all statistically insignificant, consistent with no significant comparative advantage differences for large banks between leasing and the other fixed-asset technologies for small firms. The interactions with the medium- and large-firm dummies are larger in absolute value in all cases and statistically significant in most cases, suggesting stronger comparative advantages in leasing for these firm sizes. A notable exception is that for equipment lending, neither of the interactions are statistically significant, suggesting that the comparative advantages may not differ by size class.

Panel B of Table 8 confirms and quantifies these findings in terms of predicted probabilities. The top four rows show that for small firms, none of the predicted probabilities of the loan being made by a large bank change in a statistically significant fashion as the lending shifts from LEASE to another fixed-asset technology, but the differences are larger quantitatively for the MV and EQ technologies. The second set of rows shows that for medium firms, the predicted probability of a large bank decreases in a statistically and economically significant manner when technology shifts from LEASE to any of the other fixed-asset technologies. For large firms, the findings are similar to those for medium firms, except that the differences are slightly smaller in most cases. At the bottom of the panel, we also show F-tests – one for each null hypothesis that the effect of LEASE versus one of the other fixed-asset technologies is the same across all three size classes. In each case, these are tests that of the null that the two corresponding interaction terms between firm size and the technology in question are zero. As shown, we can reject the null hypothesis in 3 of 4 cases. For EQ loans, the null cannot be rejected. As noted above, both of the individual interaction terms are statistically insignificant.¹²

Finally, we turn to Table 9, which has the results of testing for differences between the two soft technologies, relationship lending and judgment lending. We exclude the JUDGE dummy as part of the base case and test the differences in RELATE and JUDGE. The results in Panel A, column (1) (firm size

¹² We also test the differences in comparative advantages among the four collateral-based fixed-asset lending technologies and we are not able to reject the null hypothesis in any of these tests.

only) show a much different effect of bank size from Tables 6, 7, and 8 because of the limited sample here. For the relatively small number of soft technology loans, there is little difference in lending bank size between small and medium firms, but large firms are much more likely to borrow from large banks. In column (2) (lending technology only), the coefficient on RELATE is statistically insignificant, consistent with no difference in comparative advantage or disadvantage for large banks between these technologies. Column (3) (firm size and technology, no interactions) shows similar results to columns (1) and (2). In the complete specification in column (4), neither RELATE nor its interactions with firm size are statistically significant, but the interaction with large firm size is relatively large in magnitude, suggesting a possible greater relative use of this technology when large firms are involved. It is possible that these estimates could be biased by a misidentification of credit scoring. However, it is unlikely that the large bank restriction in credit scoring would affect the comparison of large bank advantages in relationship lending relative to judgment lending.

Panel B of Table 9 shows no statistically significant differences in the predicted probabilities for any of the firm size classes. Thus, we cannot reject the null hypothesis that there is no difference in the comparative advantages of large banks between the two soft technologies for any size class. The F-test is also insignificant, so we cannot reject the null of no differences across the size classes. Despite the lack of statistical significance, there are notable differences in sign and magnitude between the small and medium firms on the one hand and the large firms on the other hand. For small and medium firms, the predicted probability of borrowing from a large bank is 2.4% to 8.1% lower for a relationship loan than a judgment loan, but for a large bank, the predicted probability is 13.9% higher. This may reflect a greater relative use of relationship lending by large banks when large firms are involved. The lack of statistical significance despite the large magnitudes likely reflects the relatively small number of observations available for these tests.

The results in Table 9 also suggest small banks have similar comparative advantages in using relationship lending and judgment lending when serving small and medium firms. This finding implies that judgment lending may function somewhat as a substitute for relationship lending in the absence of strong relationships between banks and firms of these sizes. For instance, a small, young firm in need of financing may not have been in business long enough to have established a strong banking

relationship. In this situation, the loan officer may rely more on other sources of soft information, including the officer's training and personal experience to evaluate the firm's credit quality. Consistent with the arguments above, the relatively intensive use of soft information likely gives small banks a comparative advantage in this technology.

A final implication of the findings in Table 9 is the importance of separately identifying the judgment lending technology. In empirical research using the current paradigm, loans to borrowers without strong banking relationships may often be misclassified as hard technology loans. Our finding that a substantial fraction of these credits are likely to be soft technology loans that are functionally similar to relationship loans suggests a possible additional significant bias in these studies. That is, the conventional approach may not only create problems by grouping the hard technologies together, but these problems may be compounded by including a soft technology into this broad category.

Our regression results in Tables 6 – 9 are robust to a number of changes in sample and specification. First, we try dropping all of the firms with multiple loans at a single bank and then multiple loans at multiple banks, because the error terms for these loans are likely correlated. Second, we try splitting the sample between metropolitan and rural markets because of the significant differences in competitive conditions between these two environments. Third, we try adding 8 industry dummies to control for differences in transparency and loan types across industries. In all cases, the results are consistent with our main findings.¹³

7. Conclusions

We test the current paradigm in small business lending research by relaxing some of its most restrictive and unnecessary assumptions. We allow for a more general framework of multiple hard- and

¹³ We also control for bank lending type – banks that tend to specialize in small business lending, banks that specialize in real-estate lending, and banks that specialize in high-risk lending. Specifically, we include dummies for banks in the top 10% of the June 1997 commercial bank distribution of small business lending relative to total commercial and industrial (C&I) lending. This was done separately for loans with original amounts of under \$100,000, \$100,000-\$250,000, and \$250,000-\$1,000,000. We also include two dummies from the December 1997 commercial bank distribution. The first is a dummy for banks in the top 10% in terms of real estate lending relative to total C&I lending. The second is a dummy for banks in the top 10% in terms of nonperforming loans (past due at least 90 days or nonaccrual) relative to total C&I lending. In all cases, our results are robust to the inclusion of these variables. However, we exclude these variables from our main specification because they are likely to be endogenous – bank type and bank size are likely to be determined jointly.

soft-information technologies and an analysis of distinct comparative advantages for large and small banks across lending technology and firm size. We test the empirical predictions of the current paradigm using data on U.S. small businesses, the banks that lend to them, the contract characteristics of these loans, and other information.

Under the current paradigm, large banks have comparative advantages in using lending technologies based on “hard” quantitative information – such as financial statements – to lend to relatively large, transparent firms. Small banks, by contrast, have the advantage in using relationship lending based on “soft” qualitative information to lend to relatively small, opaque firms. We break these assumed linkages among bank size, lending technologies, and firm size in the current paradigm. We show that large banks’ comparative advantages extend beyond lending to large, transparent firms because hard information is available in forms other than financial statements. Thus, large banks may be able to lend to opaque small firms using hard information about the firm’s collateral or owner without using significant hard information about the firm itself. We also show that small banks’ comparative advantages extend beyond relationship lending. All lending technologies have both hard and soft components, so small banks may have advantages in some hard-information technologies based on their soft-information components. Small banks may also have a comparative advantage in judgment lending, an important soft-information technology that is neglected by the paradigm.

Our empirical analysis yields four main results, all of which conflict with the predictions of the current paradigm. First, we find that the data are inconsistent with the implication of the current paradigm that large banks have comparative advantages across all hard technologies. The data instead suggest that large banks have significant comparative advantages in only some of these technologies. Moreover, these advantages appear to differ substantially by the size of borrowing firm to which they are applied. To illustrate, among the fixed-asset lending technologies, the data suggest that large banks have clear superiority only in leasing, and that even this advantage does not extend when serving the smallest firms. These results are consistent with our relaxation of some of the assumptions of the current paradigm, under which large banks have the comparative advantage only when the hard-information components dominate for a particular technology and firm-size pair.

Second, the data appear to reject the assumption of the current paradigm that hard technologies

may be represented by the financial statement lending technology. Our results suggest that financial statement loans constitute only a small minority of hard-technology credits to small businesses. Moreover, the comparative advantages of large banks in hard technologies differ greatly across technologies, making it unclear how any one technology could be representative.

Third, our results are also inconsistent with the prediction of the current paradigm that the comparative advantage of large banks in hard technologies as a whole is increasing in firm size. We find to the contrary that the comparative advantage of large banks in hard-information lending appears to apply to small and medium firms, but not to large firms. These findings are consistent with our relaxation of some of the restrictive assumptions of the current paradigm, which allows for the possibility that banks can effectively use some forms of hard information, such as easily-valued fixed-asset collateral or credit scores, to lend to relatively small firms.

Finally, the data appear to reject the implication of the current paradigm that relationship lending is the only important soft-information technology. Our identification procedure – while admittedly requiring some fairly arbitrary assumptions – finds that the judgment lending technology based primarily on the loan officer’s training and personal experience may be employed more frequently than relationship lending. Much of the empirical research under the current paradigm may inadvertently mix judgment lending with hard technologies by using only a measure of relationship strength to distinguish relationship lending from all other technologies. Our empirical results suggest that small banks have similar comparative advantages in using both relationship lending and judgment lending to serve small and medium firms, which implies that the mixing of judgment and hard-information loans in the current paradigm may result in significantly biased results. Our findings are consistent with our relaxation of some of the restrictive assumptions of the current paradigm, under which banks may lend primarily on the basis of the loan officer’s trained judgment in the absence of sufficient hard information or a strong relationship on which to base the credit, and small banks may have comparative advantages in this technology.

The analysis has potentially important policy implications, since the current paradigm implies that the consolidation of the banking industry may result in reduced credit to the smallest, least transparent small businesses, as large banks are disadvantaged in serving these firms. When we relax

some of the most restrictive assumptions, we allow for the possibility that large banks can and do lend to these firms using hard-information lending technologies other than financial statement lending. This possibility is also consistent with the stylized facts discussed above that large banks appear to be aggressively pursuing small business credits, including loans to the smallest, least transparent firms.

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Figure 1

Identification of the Lending Technologies Used by Banks to Lend to Small Businesses
Data Sources: 1998 Survey of Small Business Finances (SSBF). December 1997 Bank Call Report

Step 1: Identifying Fixed-Asset Technologies

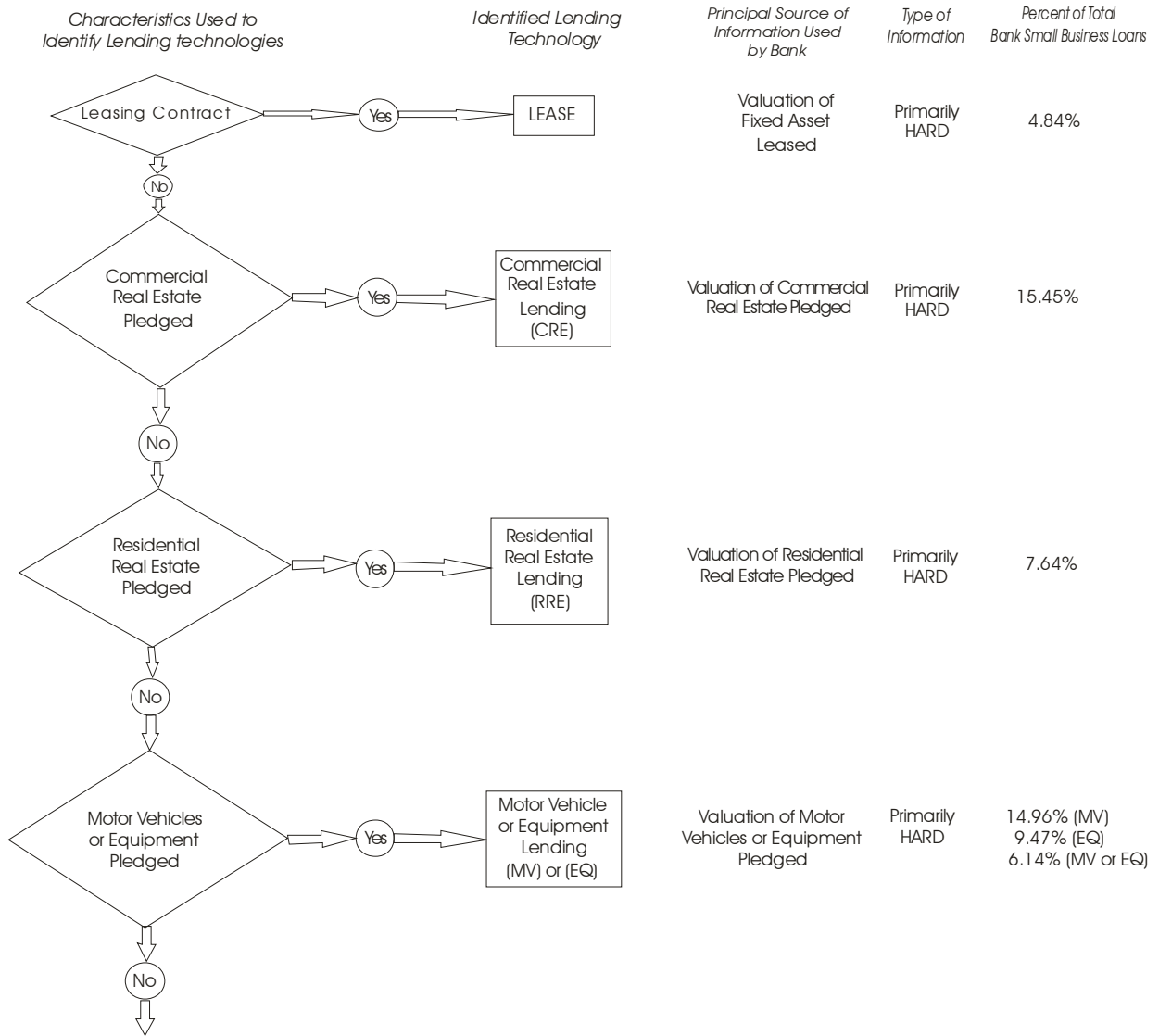
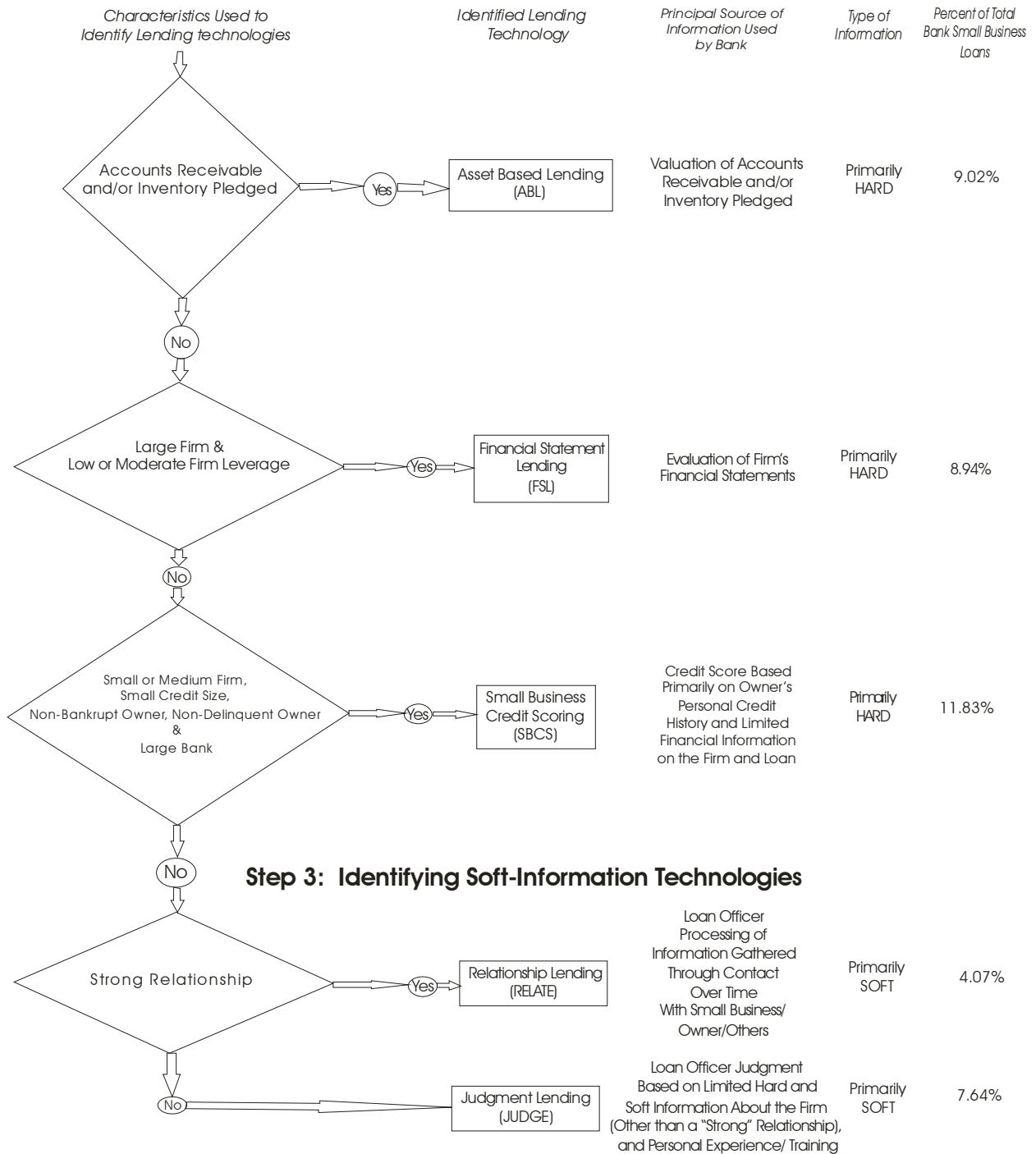


Figure 1: Continued

Step 2: Identifying Other Hard-Information Technologies



Primarily HARD Information Technologies TOTAL = 88.29%
 Primarily SOFT Information Technologies TOTAL = 11.71%

Table 1
Variables Used to Identify Bank Lending Technologies

Data Sources: 1998 Survey of Small Business Finance (SSBF); December 1997 Bank Call Reports.
 Notes: K, M, and B indicate thousands, millions, and billions, respectively.

| Variable | Description | No. Obs | Mean | Std Dev |
|---|--|---------|--------|---------|
| <i>Step 1: Variables used to identify fixed asset technologies</i> | | | | |
| Leasing Contract | Contract in which the bank owns the asset | 2460 | 0.0484 | 0.2146 |
| Commercial Real Estate Pledged | Commercial real estate pledged as collateral | 2460 | 0.1545 | 0.3614 |
| Residential Real Estate Pledged | Residential real estate pledged as collateral | 2460 | 0.1130 | 0.3166 |
| Motor Vehicles Pledged | Motor vehicles pledged as collateral | 2460 | 0.1496 | 0.3567 |
| Equipment Pledged | Equipment pledged as collateral | 2460 | 0.0947 | 0.2928 |
| Motor Vehicles and/or Equipment Pledged | MV and/or EQ pledged as collateral, but not distinguished in data | 2460 | 0.0874 | 0.2824 |
| <i>Step 2: Variables used to identify other hard-information technologies</i> | | | | |
| Accounts Receivable and/or Inventory Pledged | Accounts Receivable and/or Inventory pledged as collateral | 2460 | 0.1504 | 0.3575 |
| Large Firm | Firm total assets (TA) > \$1M | 2460 | 0.3951 | 0.4889 |
| Low or Moderate Firm Leverage | Firm liabilities/total assets \leq 0.9 | 2460 | 0.7033 | 0.4568 |
| Small or Medium Firm | Firm total assets (TA) \leq \$1M | 2460 | 0.6049 | 0.4889 |
| Small Credit Size | Max(loan amount, credit limit) \leq \$100K | 2460 | 0.6130 | 0.4871 |
| Non-Bankrupt Owner | Owner has not declared personal bankruptcy | 2460 | 0.9931 | 0.0828 |
| Non-Delinquent Owner | Owner has not been personally delinquent 60 or more days in prior 3 years | 2460 | 0.9049 | 0.2934 |
| Large Bank | Bank gross total assets (GTA) > \$1B | 2460 | 0.5984 | 0.4902 |
| <i>Step 3: Variables used to identify soft information technologies</i> | | | | |
| <i>Relationship Length</i> | | | | |
| Short Relationship | Relationship length \leq 5 years | 2460 | 0.4199 | 0.4935 |
| Medium Relationship | Relationship length > 5 years and \leq 10 years | 2460 | 0.2593 | 0.4383 |
| Long Relationship | Relationship length > 10 years | 2460 | 0.3207 | 0.4667 |
| <i>Relationship Breadth</i> | | | | |
| Checking Account | Firm has a checking account at the bank | 2460 | 0.7923 | 0.4057 |
| Exclusive Lender | Bank is firm's exclusive lender | 2460 | 0.3951 | 0.4889 |
| <i>Relationship Strength</i> | | | | |
| Strong Relationship | {Long Relationship and (Checking Account and/or Exclusive Lender)} or {Medium Relationship and (Checking Account and Exclusive Lender)} | 2460 | 0.2959 | 0.4564 |

Table 2
Frequency Distribution of Technologies Used by Banks to Lend to Small Businesses by Firm Size
(Using Identifications Shown in Figure 1)

Data Sources: 1998 Survey of Small Business Finance (SSBF); December 1997 Bank Call Reports.

Notes: All figures are in percentages, except number of loans. The 0.00 entries indicate no loans in size category by assumptions used in identifying the lending technologies. K and M indicate thousands and millions, respectively. The weighted figures are based on the sampling weights provided in the SSBF.

| | | Small Firms TA ≤\$100K (1) | Medium Firms \$100K<TA≤\$1M (2) | Large Firms \$1M<TA (3) | All Firms (4) | All Firms (Weighted) (5) | All Firms (Dollar Amounts) (6) |
|--|----------|----------------------------------|---------------------------------------|-------------------------------|------------------|--------------------------------|--------------------------------------|
| <i>Hard-Information Lending Technologies</i> | | | | | | | |
| <i>Fixed Asset Technologies</i> | | | | | | | |
| Leasing | LEASE | 4.59 | 3.50 | 6.24 | 4.84 | 4.02 | 3.07 |
| Commercial Real Estate Lending | CRE | 6.05 | 16.05 | 19.33 | 15.45 | 13.39 | 23.75 |
| Residential Real Estate Lending | RRE | 13.15 | 9.26 | 3.47 | 7.64 | 10.12 | 3.46 |
| Motor Vehicle Lending | MV | 17.54 | 16.36 | 12.39 | 14.96 | 16.25 | 1.47 |
| Equipment Lending | EQ | 4.59 | 8.74 | 12.49 | 9.47 | 8.22 | 8.95 |
| MV or EQ Lending | MV or EQ | 7.72 | 5.04 | 6.44 | 6.14 | 6.04 | 6.91 |
| Fixed Asset Totals | | 53.65 | 58.95 | 60.36 | 58.50 | 58.05 | 47.61 |
| <i>Other Hard Information Technologies</i> | | | | | | | |
| Asset-Based Lending | ABL | 2.51 | 6.34 | 14.67 | 9.02 | 6.30 | 27.17 |
| Financial Statement Lending | FSL | 0.00 | 0.00 | 21.80 | 8.94 | 4.36 | 16.11 |
| Small Business Credit Scoring | SBCS | 26.30 | 16.98 | 0.00 | 11.83 | 16.96 | 0.64 |
| Other Hard Information Totals | | 28.81 | 23.35 | 36.47 | 29.80 | 27.62 | 43.93 |
| Hard-Information Totals | | 82.46 | 82.30 | 96.83 | 88.29 | 85.66 | 91.55 |
| <i>Soft-Information Lending Technologies</i> | | | | | | | |
| Relationship Lending | RELATE | 5.43 | 6.48 | 1.09 | 4.07 | 4.73 | 5.71 |
| Judgment Lending | JUDGE | 12.11 | 11.21 | 2.08 | 7.64 | 9.61 | 2.74 |
| Soft-Information Totals | | 17.54 | 17.70 | 3.17 | 11.71 | 14.34 | 8.45 |
| Number of Loans | | 479 | 972 | 1009 | 2460 | | |
| Percent of Total Number of Loans | | 19.47 | 39.51 | 41.02 | 100.00 | | |

Table 3
Frequency Distributions of Technologies Used to Lend to Small Businesses by Bank Size
(Using Identifications Shown in Figure 1)

Data Sources: 1998 Survey of Small Business Finance (SSBF); December 1997 Bank Call Reports.

Notes: All figures are in percentages, except number of loans. The 0.00 entries indicate no loans in size category by assumptions used in identifying the lending technologies. B indicates billions.

| | | Conditional on Bank Size | | | Conditional on Lending Technology | | |
|--|----------|--------------------------|-------------|-----------|-----------------------------------|-------------|-----------|
| | | Small Banks | Large Banks | All Banks | Small Banks | Large Banks | All Banks |
| | | GTA ≤ \$1B | GTA > \$1B | (3) | GTA ≤ \$1B | GTA > \$1B | (6) |
| | | (1) | (2) | (3) | (4) | (5) | (6) |
| <i>Hard-Information Lending Technologies</i> | | | | | | | |
| <i>Fixed Asset Technologies</i> | | | | | | | |
| Leasing | LEASE | 2.02 | 6.73 | 4.84 | 16.81 | 83.19 | 100.00 |
| Commercial Real Estate Lending | CRE | 19.13 | 12.98 | 15.45 | 49.74 | 50.26 | 100.00 |
| Residential Real Estate Lending | RRE | 8.30 | 7.20 | 7.64 | 43.62 | 56.38 | 100.00 |
| Motor Vehicle Lending | MV | 17.31 | 13.38 | 14.96 | 46.47 | 53.53 | 100.00 |
| Equipment Lending | EQ | 11.54 | 8.08 | 9.47 | 48.93 | 51.07 | 100.00 |
| MV or EQ Lending | MV or EQ | 8.30 | 4.69 | 6.14 | 54.30 | 45.70 | 100.00 |
| Fixed Asset Totals | | 66.60 | 53.06 | 58.50 | 45.73 | 54.27 | 100.00 |
| <i>Other Hard Information Technologies</i> | | | | | | | |
| Asset-Based Lending | ABL | 6.17 | 10.94 | 9.02 | 27.48 | 72.52 | 100.00 |
| Financial Statement Lending | FSL | 7.19 | 10.12 | 8.94 | 32.27 | 67.73 | 100.00 |
| Small Business Credit Scoring | SBCS | 0.00 | 19.77 | 11.83 | 0.00 | 100.00 | 100.00 |
| Other Hard Information Totals | | 13.36 | 40.83 | 29.80 | 18.01 | 81.99 | 100.00 |
| Hard-Information Totals | | 79.96 | 93.89 | 88.30 | 36.37 | 63.63 | 100.00 |
| <i>Soft-Information Lending Technologies</i> | | | | | | | |
| Relationship Lending | RELATE | 7.59 | 1.70 | 4.07 | 75.00 | 25.00 | 100.00 |
| Judgment Lending | JUDGE | 12.45 | 4.42 | 7.64 | 65.43 | 34.57 | 100.00 |
| Soft-Information Totals | | 20.04 | 6.11 | 11.71 | 68.75 | 31.25 | 100.00 |
| Column Totals | | 100.00 | 100.00 | 100.00 | 40.16 | 59.84 | 100.00 |
| Percent of Total | | 40.16 | 59.84 | 100.00 | 40.16 | 59.84 | 100.00 |
| Number of Loans | | 988 | 1472 | 2460 | 988 | 1472 | 2460 |

Table 4
Frequency Distributions of Technologies Used to Lend to Small Businesses
By Bank Size Conditional on Firm Size
(Using Identifications Shown in Figure 1)

Data Sources: 1998 Survey of Small Business Finance (SSBF); December 1997 Bank Call Reports.

All figures are in percentages, except number of loans. The 0.00 entries indicate no loans in firm size-bank category by assumptions used in identifying technologies. K, M and B indicate thousands, millions, and billions, respectively.

| | | Small Firms TA ≤ \$100K | | Medium Firms \$100K < TA ≤ \$1M | | Large Firms \$1M < TA | |
|--|----------|----------------------------|---------------------------|------------------------------------|---------------------------|---------------------------|---------------------------|
| | | Small Banks GTA ≤ \$1B | Large Banks GTA > \$1B | Small Banks GTA ≤ \$1B | Large Banks GTA > \$1B | Small Banks GTA ≤ \$1B | Large Banks GTA > \$1B |
| | | (1) | (2) | (3) | (4) | (5) | (6) |
| <i>Hard-Information Lending Technologies</i> | | | | | | | |
| <i>Fixed Asset Technologies</i> | | | | | | | |
| Leasing | LEASE | 36.36 | 63.64 | 17.65 | 82.35 | 9.52 | 90.48 |
| Commercial Real Estate Lending | CRE | 44.83 | 55.17 | 58.97 | 41.03 | 43.08 | 56.92 |
| Residential Real Estate Lending | RRE | 38.10 | 61.90 | 50.00 | 50.00 | 37.14 | 62.86 |
| Motor Vehicle Lending | MV | 45.24 | 54.76 | 49.06 | 50.94 | 44.00 | 56.00 |
| Equipment Lending | EQ | 54.55 | 45.45 | 63.53 | 39.47 | 38.10 | 61.90 |
| MV or EQ Lending | MV or EQ | 64.86 | 35.14 | 67.35 | 32.65 | 38.46 | 61.54 |
| Fixed Asset Totals | | 46.30 | 53.70 | 53.75 | 46.25 | 37.93 | 62.07 |
| <i>Other Hard Information Technologies</i> | | | | | | | |
| Asset-Based Lending | ABL | 33.33 | 66.67 | 37.10 | 62.90 | 22.97 | 77.03 |
| Financial Statement Lending | FSL | 0.00 | 0.00 | 0.00 | 0.00 | 32.27 | 67.73 |
| Small Business Credit Scoring | SBCS | 0.00 | 100.00 | 0.00 | 100.00 | 0.00 | 0.00 |
| Other Hard Information Totals | | 2.90 | 97.10 | 10.13 | 89.87 | 28.53 | 71.47 |
| Hard-Information Totals | | 31.14 | 68.86 | 41.38 | 58.63 | 34.39 | 65.61 |
| <i>Soft-Information Lending Technologies</i> | | | | | | | |
| Relationship Lending | RELATE | 88.46 | 11.54 | 76.19 | 23.81 | 36.36 | 63.64 |
| Judgment Lending | JUDGE | 72.41 | 27.59 | 66.97 | 33.03 | 38.10 | 61.90 |
| Soft-Information Totals | | 77.38 | 22.62 | 70.35 | 29.65 | 37.50 | 62.50 |
| All Technologies | | 39.25 | 60.75 | 46.50 | 53.50 | 34.49 | 65.51 |
| Number of Loans | | 188 | 291 | 452 | 520 | 348 | 661 |
| Percent of 2460 Grand Total | | 7.64 | 11.83 | 18.37 | 21.14 | 14.15 | 26.87 |

Table 5
Summary Statistics For Variables Used in Regressions

Data Sources: 1998 Survey of Small Business Finance (SSBF); December 1997 Bank Call Reports; 1997 Summary of Deposits.
 Notes: K, M, and B indicate thousands, millions, and billions, respectively.

| Variable | Description | (1) | | (2) | | (3) | | (4) | |
|--|--|-------------|---------|-------------|---------|-------------|---------|------------|---------|
| | | Mean | Std Dev | Mean | Std Dev | Mean | Std Dev | Mean | Std Dev |
| <i>Bank Size</i> | | | | | | | | | |
| Large Bank | Bank gross total assets (GTA) > \$1B | 0.593 | 0.491 | 0.543 | 0.498 | 0.551 | 0.498 | 0.313 | 0.465 |
| <i>Firm Size</i> | | | | | | | | | |
| Small Firm | Firm total assets (TA) ≤ \$100K | 0.195 | 0.396 | 0.164 | 0.370 | 0.172 | 0.377 | 0.289 | 0.454 |
| Medium Firm | Firm total assets (TA) > \$100K and ≤ \$1M | 0.396 | 0.490 | 0.372 | 0.483 | 0.407 | 0.492 | 0.600 | 0.491 |
| Large Firm | Firm total assets (TA) > \$1M | 0.409 | 0.492 | 0.464 | 0.499 | 0.421 | 0.494 | 0.111 | 0.318 |
| <i>Identified Lending Technologies</i> | | | | | | | | | |
| <i>Hard Information: Other Fixed-Asset Lending vs. Leasing</i> | | | | | | | | | |
| Leasing | LEASE | | | | | 0.091 | 0.288 | | |
| Commercial Real Estate | CRE | | | | | 0.296 | 0.456 | | |
| Residential Real Estate | RRE | | | | | 0.144 | 0.351 | | |
| Motor Vehicle Loan | MV | | | | | 0.287 | 0.452 | | |
| Equipment Loan | EQ | | | | | 0.182 | 0.386 | | |
| <i>Hard Information vs. Soft Information</i> | | | | | | | | | |
| Hard | LEASE, CRE, RRE, MV, EQ, MV or EQ, ABL, FSL, or SBCS | 0.882 | 0.323 | | | | | | |
| Soft | RELATE or JUDGE | 0.118 | 0.323 | | | | | | |
| Hard (without SBCS) | LEASE, CRE, RRE, MV, EQ, MV or EQ, ABL, or FSL | | | 0.866 | 0.341 | | | | |
| Soft | RELATE, or JUDGE | | | 0.134 | 0.341 | | | | |
| <i>Soft Information: Relationship Lending vs. Judgment Lending</i> | | | | | | | | | |
| Relationship Lending | RELATE | | | | | | | 0.341 | 0.475 |
| Judgment Lending | JUDGE | | | | | | | 0.659 | 0.475 |
| <i>Market Characteristics</i> | | | | | | | | | |
| Large Bank Branch Market Share | Share of large bank branches in market | 0.584 | 0.261 | 0.570 | 0.495 | 0.564 | 0.269 | 0.535 | 0.275 |
| Herfindahl | Concentration of bank deposits in market | 0.211 | 0.106 | 0.211 | 0.408 | 0.218 | 0.115 | 0.207 | 0.095 |
| MSA | Firm in MSA or NECMA | 0.721 | 0.449 | 0.708 | 0.455 | 0.678 | 0.467 | 0.690 | 0.463 |
| Observations | | 2434 | | 2145 | | 1269 | | 287 | |

Table 6
Tests of Hard-Information vs. Soft-Information Lending Technologies
(Panel A) Regression Results

Dependent variable: Large Bank
 Logit Regression

"Hard" in this table is the group of all hard-information lending technologies.

| | (1) | (2) | (3) | (4) |
|--------------------------------|----------------------|----------------------|----------------------|----------------------|
| <i>Firm Size</i> | | | | |
| Medium Firm | -0.428 [3.376]*** | | -0.442 [3.380]*** | 0.182 [0.549] |
| Large Firm | 0.044 [0.347] | | -0.157 [1.181] | 1.603 [3.293]*** |
| <i>Technology</i> | | | | |
| Hard | | 1.389 [9.528]*** | 1.344 [9.003]*** | 2.073 [6.759]*** |
| <i>Interactions</i> | | | | |
| Medium Firm * Hard | | | | -0.753 [2.075]** |
| Large Firm * Hard | | | | -1.927 [3.799]*** |
| <i>Market Characteristics</i> | | | | |
| Large Bank Branch Market Share | 3.300 [16.072]*** | 3.293 [15.788]*** | 3.33 [15.905]*** | 3.341 [15.896]*** |
| Herfindahl | 0.571 [1.133] | 0.544 [1.065] | 0.466 [0.911] | 0.457 [0.889] |
| MSA | 0.294 [2.370]** | 0.334 [2.651]*** | 0.307 [2.430]** | 0.297 [2.341]** |
| Pseudo R ² | 0.135 | 0.157 | 0.161 | 0.165 |
| Observations | 2434 | 2434 | 2434 | 2434 |

t-statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Base case: Small Firm, Soft-Information Technology

Table 6**Tests of Hard-Information vs. Soft-Information Lending Technologies****(Panel B) Tests of Predicted Probabilities of Large Bank by Firm Size and Lending Technology**

Based on the results from Panel A, we calculate the predicted probability of a firm borrowing from a large bank conditional on firm size and technology type. We then test the statistical significance of the effect of hard-information technologies vs. soft-information technologies (Hard - Soft) for each firm size class. The t-statistic for each test is shown in brackets. We also perform an F-test on whether the effect of hard-information technologies vs. soft-information technologies is different across firm size classes.

| | (1) Soft | (2) Hard | (3) Hard - Soft |
|---|-------------|-------------|--------------------|
| Small Firm | 0.247 | 0.723 | 0.476 [6.76]*** |
| Medium Firm | 0.283 | 0.596 | 0.313 [6.76]*** |
| Large Firm | 0.620 | 0.654 | 0.034 [0.36] |
| F-Test for differences across size classes (2 restrictions) | | | 14.46*** |

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7
Tests of Hard-Information vs. Soft-Information Lending Technologies
with Small Business Credit Scoring Loans Dropped

(Panel A) Regression Results

Dependent variable: Large Bank

Logit Regression

"Hard" in this table is the group of all hard-information lending technologies, excluding Small Business Credit Scoring (SBCS). The SBCS loans have been dropped.

| | (1) | (2) | (3) | (4) |
|--------------------------------|-------------|-------------|-------------|-------------|
| <i>Firm Size</i> | | | | |
| Medium Firm | -0.221 | | -0.242 | 0.188 |
| | [1.562] | | [1.682]* | [0.567] |
| Large Firm | 0.602 | | 0.422 | 1.603 |
| | [4.343]*** | | [2.944]*** | [3.309]*** |
| <i>Technology</i> | | | | |
| Hard | | 1.159 | 0.936 | 1.456 |
| | | [7.926]*** | [6.177]*** | [4.674]*** |
| <i>Interactions</i> | | | | |
| Medium Firm * Hard | | | | -0.54 |
| | | | | [1.464] |
| Large Firm * Hard | | | | -1.315 |
| | | | | [2.586]*** |
| <i>Market Characteristics</i> | | | | |
| Large Bank Branch Market Share | 3.183 | 3.243 | 3.222 | 3.228 |
| | [14.556]*** | [14.759]*** | [14.545]*** | [14.546]*** |
| Herfindahl | 0.592 | 0.481 | 0.505 | 0.507 |
| | [1.122] | [0.905] | [0.951] | [0.952] |
| MSA | 0.269 | 0.315 | 0.278 | 0.271 |
| | [2.039]** | [2.377]** | [2.083]** | [2.029]** |
| Pseudo R ² | 0.144 | 0.144 | 0.157 | 0.160 |
| Observations | 2145 | 2145 | 2145 | 2145 |

t-statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Base case: Small Firm, Soft-Information Technologies

Table 7
Tests of Hard-Information vs. Soft-Information Lending Technologies
with Small Business Credit Scoring Loans Dropped

(Panel B) Tests of Predicted Probabilities of Large Bank by Firm Size and Lending Technology

Based on the results from Panel A, we calculate the predicted probability of a firm borrowing from a large bank conditional on firm size and technology type. We then test the statistical significance of the effect of hard-information technologies vs. soft-information technologies (Hard - Soft) for each firm size class. The t-statistic for each test is shown in brackets. We also perform an F-test on whether the effect of hard-information technologies vs. soft-information technologies is different across firm size classes.

| | (1) Soft | (2) Hard | (3) Hard - Soft |
|---|-------------|-------------|--------------------|
| Small Firm | 0.239 | 0.574 | 0.335 [4.67]*** |
| Medium Firm | 0.275 | 0.619 | 0.344 [4.63]*** |
| Large Firm | 0.610 | 0.643 | 0.033 [0.35] |
| F-Test for differences across size classes (2 restrictions) | | | 2.45 |

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8
Tests of Other Fixed-Asset Lending Technologies vs. Leasing
(Panel A) Regression Results

Dependent Variable: Large Bank
 Logit Regression

| | (1) | (2) | (3) | (4) |
|---------------------------------------|----------------------|----------------------|----------------------|----------------------|
| <i>Firm Size</i> | | | | |
| Medium Firm | -0.530 [2.949]*** | | -0.431 [2.340]** | 0.908 [1.336] |
| Large Firm | -0.026 [0.143] | | 0.086 [0.451] | 1.527 [2.323]** |
| <i>Technology</i> | | | | |
| Commercial Real Estate Lending (CRE) | | -1.439 [5.060]*** | -1.404 [4.900]*** | 0.065 [0.102] |
| Residential Real Estate Lending (RRE) | | -1.154 [3.756]*** | -1.056 [3.401]*** | 0.178 [0.317] |
| Motor Vehicle Loan (MV) | | -1.246 [4.375]*** | -1.182 [4.128]*** | -0.171 [0.318] |
| Equipment Loan (EQ) | | -1.361 [4.575]*** | -1.349 [4.503]*** | -0.510 [0.765] |
| <i>Interactions</i> | | | | |
| Medium Firm * CRE | | | | -1.877 [2.281]** |
| Medium Firm * RRE | | | | -1.685 [2.177]** |
| Medium Firm * MV | | | | -1.097 [1.481] |
| Medium Firm * EQ | | | | -1.351 [1.575] |
| Large Firm * CRE | | | | -1.870 [2.335]** |
| Large Firm * RRE | | | | -1.628 [1.994]** |
| Large Firm * MV | | | | -1.716 [2.359]** |
| Large Firm * EQ | | | | -1.085 [1.310] |
| <i>Market Characteristics</i> | | | | |
| Large Bank Branch Market Share | 3.164 [11.524]*** | 3.094 [11.258]*** | 3.107 [11.218]*** | 3.130 [11.240]*** |
| Herfindahl | 0.566 [0.895] | 0.652 [1.027] | 0.657 [1.030] | 0.722 [1.119] |
| MSA | 0.159 [0.969] | 0.167 [1.007] | 0.128 [0.770] | 0.135 [0.802] |
| Pseudo R ² | 0.126 | 0.135 | 0.143 | 0.151 |
| Observations | 1269 | 1269 | 1269 | 1269 |

t-statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Base case: Small Firm, Leasing Technology (LEASE)

Table 8
Tests of Other Fixed-Asset Lending Technologies vs. Leasing
(Panel B) Tests of Predicted Probabilities of Large Bank by Firm Size and Lending Technology

Based on the results from Panel 1, we calculate the predicted probability of a firm borrowing from a large bank conditional on firm size and fixed-asset technology type. We then test the statistical significance of the effect of each fixed-asset lending technology vs. leasing (Other Fixed-Asset Technologies - Leasing) for each firm size class. Other than leasing, the fixed-asset lending technologies include commercial real estate lending (CRE), residential real estate lending (RRE), motor vehicle lending (MV), and equipment lending (EQ). The t-statistic for each test is shown in brackets. We also perform F-tests on whether the effect of each of the other fixed-asset lending technologies vs. leasing is different across firm size classes.

| | (1) Leasing | (2) Other Fixed-Asset Lending Technologies | (3) Other Fixed-Asset - Leasing Lending Technologies |
|---|----------------|--|--|
| Small Firm | 0.624 | CRE | 0.639 0.015 [0.10] |
| | 0.624 | RRE | 0.665 0.041 [0.32] |
| | 0.624 | MV | 0.231 -0.393 [0.32] |
| | 0.624 | EQ | 0.499 -0.125 [0.77] |
| Medium Firm | 0.804 | CRE | 0.402 -0.402 [3.53]*** |
| | 0.804 | RRE | 0.477 -0.327 [2.82]*** |
| | 0.804 | MV | 0.198 -0.606 [2.48]** |
| | 0.804 | EQ | 0.39 -0.414 [3.45]*** |
| Large Firm | 0.884 | CRE | 0.557 -0.327 [3.78]*** |
| | 0.884 | RRE | 0.642 -0.242 [2.44]** |
| | 0.884 | MV | 0.199 -0.685 [3.84]*** |
| | 0.884 | EQ | 0.608 -0.276 [3.24]*** |
| F-Test for differences across size classes (2 restrictions) | | CRE | [6.55]** |
| | | RRE | [5.84]* |
| | | MV | [5.64]* |
| | | EQ | [2.65] |

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9
Tests of Relationship Lending vs. Judgment Lending
(Panel A) Regression Results

Dependent Variable: Large Bank
 Logit Regression

| | (1) | (2) | (3) | (4) |
|--------------------------------|------------|------------|------------|------------|
| <i>Firm Size</i> | | | | |
| Medium Firm | 0.139 | | 0.152 | 0.059 |
| | [0.686] | | [0.661] | [0.880] |
| Large Firm | 1.585 | | 1.597 | 1.283 |
| | [0.002]*** | | [0.002]*** | [0.030]** |
| <i>Technology</i> | | | | |
| Relationship Lending (RELATE) | | -0.102 | -0.133 | -0.562 |
| | | [0.741] | [0.678] | [0.448] |
| <i>Interactions</i> | | | | |
| Medium Firm * RELATE | | | | 0.425 |
| | | | | [0.612] |
| Large Firm * RELATE | | | | 1.130 |
| | | | | [0.336] |
| <i>Market Characteristics</i> | | | | |
| Large Bank Branch Market Share | 4.208 | 4.163 | 4.169 | 4.158 |
| | [0.000]*** | [0.000]*** | [0.000]*** | [0.000]*** |
| Herfindahl | -2.271 | -2.317 | -2.204 | -2.398 |
| | [0.324] | [0.300] | [0.341] | [0.307] |
| MSA | 0.408 | 0.452 | 0.407 | 0.42 |
| | [0.371] | [0.309] | [0.373] | [0.360] |
| Pseudo R ² | 0.204 | 0.169 | 0.204 | 0.207 |
| Observations | 287 | 287 | 287 | 287 |

t-statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Base case: Small Firm, Judgment Lending (JUDGE)

Table 9**Tests of Relationship Lending vs. Judgment Lending****(Panel B) Tests of Predicted Probabilities of Large Bank by Firm Size and Lending Technology**

Based on the results from Panel 1, we calculate the predicted probability of a firm borrowing from a large bank conditional on firm size and soft-information technology type. We then test the statistical significance of the effect of relationship lending vs. judgment lending (Relationship Lending - Judgment Lending) for each firm size class. The t-statistic for each test is shown in brackets. We also perform an F-test on whether the effect of relationship lending vs. judgment lending is different across firm size classes.

| | (1) Judgment Lending | (2) Relationship Lending | (3) Relationship - Judgment Lending |
|---|----------------------------|--------------------------------|---|
| Small Firm | 0.217 | 0.136 | -0.081 [0.61] |
| Medium Firm | 0.228 | 0.204 | -0.024 [0.35] |
| Large Firm | 0.499 | 0.638 | 0.139 [0.62] |
| F-Test for differences across size classes (2 restrictions) | | | 0.930 |

* significant at 10%; ** significant at 5%; *** significant at 1%