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Abstract: The literature has documented a positive relationship between the use of credit scoring for small business loans and small business credit availability, broadly defined. However, this literature is hampered by the fact that all of the studies are based on a single 1998 survey of the very largest U.S. banking organizations. This paper addresses a number of deficiencies in the extant literature by employing data from a new survey on the use of credit scoring in small business lending, primarily by community banks. The survey evidence suggests that the use of credit scores in small business lending by community banks is surprisingly widespread. Moreover, the scores employed tend to be the consumer credit scores of the small business owners rather than the more encompassing small business credit scores that include data on the firms as well as on the owners. Our empirical analysis suggests that credit scoring is associated with increased small business lending after a learning period, with no material change in the quality of the loan portfolio. However, these quantity and quality results appear to vary depending on the way in which credit scores are implemented in the underwriting process.

JEL classification: G21, G28, L23

Key words: banks, small business, credit scoring

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The Surprising Use of Credit Scoring in Small Business Lending by "Community Banks" and the Attendant Effects on Credit Availability and Risk

I. Introduction

Commercial bank lending to small businesses has received a great deal of research attention over the past two decades. The overriding issue in this literature is one of credit availability, given that small firms have historically faced significant difficulties in accessing funding for creditworthy (i.e., positive net present value) projects due to a lack of credible information. Small businesses are typically much more informationally opaque than large corporations because small firms often do not have certified audited financial statements to yield credible financial information on a regular basis. As well, these firms typically do not have publicly traded equity or debt, yielding no market prices or public ratings that might suggest their quality. To address the informational opacity problem, financial institutions use a number of different lending technologies (e.g., Berger and Udell 2006).

One lending technology that has recently received considerable research attention is small business credit scoring (SBCS). This technology confronts the opacity problem by combining personal financial data about the owner of the business with the relatively limited information about the firm using statistical methods to predict future credit performance. Consumer credit scoring (CCS) has been widely used for many years in retail credit markets (e.g., mortgages, credit cards, and automobile credits), but SBCS is a more recent phenomenon. Most large U.S. banks did not adopt SBCS until the mid-1990s due to concerns regarding firm heterogeneity and nonstandardized loan documentation (e.g., Mester 1997). As discussed below, some banks instead use the consumer credit scores of small business owners to evaluate small business loan applications. The application of CCS to small business lending has not been previously studied.

The empirical literature studying the effects of SBCS has documented significant favorable effects of this lending technology on small business credit availability, broadly defined. Specifically, the adoption of SBCS is empirically associated with 1) increases in the quantity of lending (Frame, Srinivasan, and Woosley 2001, Frame, Padhi, and Woosley 2004, Berger, Frame, and Miller 2005); 2) more lending to relatively opaque, risky borrowers (Berger, Frame, and Miller 2005); 3) lending within low-income as well as high-income areas (Frame, Padhi, and Woosley 2004); and 4) lending over greater distances (DeYoung, Glennon, and Nigro 2008).[1,2] See Berger and Frame (2007) for a more comprehensive review of these studies.

While the extant research provides some important information about SBCS, this literature is hampered by the fact that all of the empirical studies are based on a single survey of the largest U.S. banking organizations conducted by the Federal Reserve Bank of Atlanta in January 1998.[3] Thus, the research to date is all subject to the same set of sample selection issues, is able to examine only the very largest banking organizations (99 of the 200 largest), and studies only the period up to January 1998 when the application of this technology was relatively new and adoption rates were relatively low. At that time, only 62% of the very largest banking organizations employed the SBCS technology. Today, however, anecdotal evidence suggests that the vast majority of large banks use SBCS and smaller institutions are making the adoption decisions. In addition, the 1998 survey queried only about the use of SBCS, and did not investigate the use of CCS in making small business lending decisions. Prior studies were also unable to examine the effect of credit scoring on the quality of the loan portfolio because for large organizations, the amount of scored loans is small relative to the size of the commercial and industrial loan portfolio, and loan quality information is available only for the entire commercial and industrial loan portfolio.

This study addresses a number of the deficiencies in the extant literature by employing data from a new survey of the use of credit scoring in small business lending. The 2005 survey was sponsored by the U.S. Small Business Administration's Office of Advocacy and covers 330 institutions, most of which are small commercial banks with assets under $1 billion, the traditional cutoff for "community banks" (e.g., DeYoung, Hunter, and Udell 2004). Hence, the

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[1] In cases in which SBCS is used in conjunction with other lending technologies, it is also shown to result in increased loan maturity (Berger, Espinosa-Vega, Frame, and Miller 2005) and reduced collateral requirements (Berger, Espinosa-Vega, Frame, and Miller 2006).

[2] These findings are also consistent with small business lending at greater distances by large banks found by other researchers without access to data on which lending technologies the banks use (e.g., Petersen and Rajan 2002, Hannan 2003, Brevoort 2006, Brevoort and Hannan 2006). However, the increased distances in these studies may also reflect the use of other transactions technologies that do not require close contact with the firm.

[3] See Frame, Srinivasan, and Woosley (2001) for detailed information about the original SBCS survey.

new data allows us to examine the extent to which credit scoring technology for small business lending has diffused "down the food chain" to small banks and whether the adoption and use of scoring technology results in increased small business credit availability by these community-based institutions, as it appears to have done for the largest banking organizations.

This new survey data also provides us with the ability to examine two additional important issues. First, the survey provides information for the first time about bank use of CCS as well as SBCS in small business lending. As shown below, CCS appears to play an especially important role in the evaluation of small business loan applications at community banks. Second, our focus on small banks allows us to match the survey data with Call Report data on nonperforming loans in order to conduct the first investigation of the effect of credit scoring on the quality of the small business credits. This, in turn, allows us to draw some limited inferences about prudential concerns regarding these institutions.

Thus, this paper makes three main contributions to the literature. The first is to provide information from the new survey on the adoption and type of credit scoring used in small business lending by community banks with under $1 billion in assets. By way of preview, we find some quite surprising results. As of 2005, almost one-half of the community banks surveyed (46%) were using some form of credit scoring in their small business lending decisions, and many of these banks had been using the technology for a long period of time (an average of 6.4 years for those reporting adoption dates). These observations run contrary to the vision of the current small business lending paradigm under which community banks focus on the use of soft information lending technologies, such as relationship lending, rather than hard-information technologies, such as credit scoring (e.g., Berger and Udell 2006).[4] In addition, we find that of the banks using credit scoring, 86% exclusively use consumer scores for the principal owner of the firm, rather than SBCS which utilizes information about both the principal owner and the firm. In most other cases (12%), community banks use both CCS and SBCS, i.e., a combination of consumer and business scores. Use of SBCS alone by community banks is quite rare (2%).

The second contribution of the paper is to study the effects of credit scoring on small business

[4] Additional survey findings that are not surprising are: (1) in most cases community banks purchase scores externally, rather than using internal models, and (2) community banks generally do not use the scores to make automated decisions regarding acceptance/rejection of the loan applications.

credit availability for community banks by examining the outcomes in terms of small business lending quantities from the Call Report. We specifically look at the dollar value of banks' commercial and industrial (C&I) loans outstanding under $100,000 ($100K) from the June Call Report as function of whether the bank has adopted credit scoring, how long the bank has been using credit scoring, whether the bank uses credit scores to automatically approve/reject loan applications, and whether the bank uses CCS or SBCS. By way of preview, the results suggest that credit scoring is associated with an increase in credit availability for credits of up to $100K and this increase manifests itself over time as community banks appear to ride a learning curve in using the technology. These results, however, appear to be limited to the majority of community bank credit scorers that use CCS, rather than SBCS, and use it to supplement other lending technologies.

Our third contribution is to examine for the first time the effects of credit scoring on the quality of the banks' loans by studying variation in their nonperforming C&I loans (past due 90 or more days or in nonaccrual status) as a proportion of total C&I loans as reported on the Call Report. The effect on loan quality reflects both the screening of loan applicants using the credit scoring techniques as well as any associated differences in monitoring after the loans are extended. This analysis is based on the assumption that the scored loans make up a significant portion of the bank's C&I loan portfolio, given that community banks tend to specialize in small business loans. Such an analysis was not possible in earlier studies because the large banks studied tend to have most of their C&I loan dollars in larger credits. By way of preview, the data suggest that banks that use credit scoring tend to have no more loan performance problems than other banks, despite the observed increase in lending to presumably more marginal borrowers. Again, these results are limited to the majority of community bank credit scoring banks that apply CCS, rather than SBCS, and use the technology to supplement other lending technologies.

The remainder of the paper is organized as follows. Section 2 gives our descriptive statistics on the adoption and use of credit scoring by community banks for small business lending. Section 3 describes our econometric model for analyzing small business loan quantity and quality. Section 4 gives our model estimation results, and Section 5 concludes.

II. Survey Data

The primary data used in our analysis comes from a new survey of U.S. banks' use of credit scoring methods for evaluating small business credits. The survey was conducted by Analytic Focus LLC during the fourth quarter of 2005 and was sponsored by the U.S. Small Business Administration. A comprehensive overview of the survey methodology and results are described in Cowan and Cowan (2006).

The survey queried a nationally representative, stratified sample of 1,500 banks of which 330 (22%) complied with the information request. The survey sample was selected in the following manner. The researchers first identified the set of 8,182 banks that completed June 2004 Call Reports. This group was then matched to an FDIC-provided list of banks active at the time of the 2005 survey, which reduced the initial sample to 7,950. This group of institutions was then further pared by 1,666, as banks not reporting any small business lending activity (both commercial real estate and commercial and industrial lending) in the June 2004 Call Report (Schedule RC-C Part II) and US branches of foreign banks were eliminated. This left 6,284 banks: 5,887 commercial banks, 334 state chartered savings banks, and 63 cooperative banks.

For sampling, the population of banks was stratified using three variables: (1) bank size, (2) total small commercial real estate lending as a proportion of the asset portfolio, and (3) the proportion of small commercial and industrial lending as a proportion of the asset portfolio. Four bank-size groups were created: total assets less than \$100 million; total assets from \$100 million to less than \$500 million; total assets from \$500 million to less than \$1 billion; and total assets greater than or equal to \$1 billion. Banks were also sorted by the two "small business lending intensity" measures into four additional categories capturing their commitment to small business lending. Ultimately, Analytic Focus drew a sample of 1,500 banks based on the four size groups as well as a composite variable intended to measure the institution's commitment to small business lending.[5]

[5] A "commitment to small business lending" was measured across two variables: (1) the ratio of loans secured by non-farm, nonresidential properties to total assets, and (2) the ratio of C&I loans to total assets. From these ratios, categorical variables were created (C1 and C2). Each took a value of one if the ratio was less than the median, a value of two if the ratio was between the median and the third quartile, a value of three if the ratio was between the

Of the 330 respondents to the survey, 156 (47 percent) reported using credit scores to underwrite small business credit as of the date of the survey. Table 1 presents these results broken out by the four bank size strata; the type of credit scoring used; and the size of the credit scored. Four important pieces of information emerge. First, given the distribution of U.S. bank assets and the stratification approach employed, the vast majority of institutions surveyed (88%) and responding to the inquiry (91%) are community banks with $1 billion or less in total assets. In our empirical analysis below, we focus exclusively on this set of institutions. Second, credit scores are surprisingly widely employed by community banks when underwriting small business loans. For loans under $50,000, 138 of the 299 community banks (46%) reported using credit scores in the underwriting process. Third, community banks rely much more on CCS than SBCS for small business credit. This may be driven by cost considerations and/or perhaps that their small business customers are not covered by the commercial credit information repositories. Fourth, consistent with the extant literature, credit scores are more often employed for smaller commercial credits – particularly those under $50,000. Notably, community banks that use credit scores in their small business loan underwriting tend to use it more often for credits above $100,000 compared to the large institutions responding to the 1998 survey. This may be related to the finding discussed below that community banks tend to more often use credit scores to supplement other lending technologies, rather than relying on the credit scoring technology alone.

[Table 1 about here.]

Non-response bias is a natural concern whenever one is working with survey data with a fairly low 22 percent response rate. To examine this issue, we conducted difference-in-means tests across the four stratification variables for responders and non-responders. We could not reject the null hypothesis that the means were the same; thereby suggesting that non-response

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third quartile and the 95th percentile, and a value of four if the ratio was greater than the 95th percentile. The sample strata (S) were then based on joint membership in categories C1 and C2 using the rule that S = min[C1, C2].

bias is not an issue.

Table 2 provides some additional intertemporal information about community banks' adoption of credit scoring techniques for small business lending. Remarkably, 18 community bank respondents that use credit scores for small business loans noted that they have been doing so since at least 1994. As reported in the 1998 survey, most of the very large banks did not adopt SBCS until 1995, when Fair, Isaac and Company introduced its first SBCS model (e.g., Berger, Frame, and Miller 2005). Also notable is that there is no clear adoption pattern since that time.

[Table 2 about here.]

We also examined differences between community banks that have adopted credit scoring for small business loans and those that have not. Specifically, using the June 1993 data, we compared gross total assets, the ratio of the quantity of commercial and industrial loans under $100,000 to gross total assets, and the ratio of total equity to gross total assets. Using t-tests, we could not reject the null hypothesis that the means of each of three variables was equal across the two groups (not shown in tables). This tends to allay concerns about the potential endogeneity of the credit scoring adoption decision.

Table 3 provides some information about whether community banks use credit scores to automatically approve or reject small business applicants – "auto decision banks" – or simply as an additional piece of underwriting information – "supplementing banks."[6] Not surprisingly, most banks say that they use credit scores as an additional piece of information in the underwriting decision. Only 29 institutions, or 17% of community bank responders, report using credit scores to automatically approve or reject applications; and this is largely relegated only to very small loans under $50,000. In contrast, about 42% of the large institutions responding to the 1998 survey were auto decision banks (Frame, Srinivasan, and Woosley 2001).

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[6] In practice, all auto decision banks allow for some judgmental overrides, and all supplementing banks use some rules for automatic rejections.

[Table 3 about here.]

To summarize some of the survey evidence, community banks use credit scoring technology in small business lending to a much greater degree than expected. The vast majority of these banks rely on CCS, or consumer credit scores of the small business owner, rather than SBCS, or scores of the small businesses themselves. Surprisingly, a number of community banks adopted a form of credit scoring for small business lending prior to the adoption of SBCS by most of the very largest banks. Consistent with the findings for the largest banks, community banks tend to use credit scoring more for smaller credits, particularly for loans under $50,000. Finally, even community banks that adopt credit scoring for small business lending tend to continue to use other lending technologies and employ credit scoring to supplement the use of these other technologies.

III. Data and Empirical Specifications

We combine information gleaned from the credit scoring survey described above with Call Report data in order to study the empirical relationship between community banks' use of credit scoring for small business loan applications and the quantity and quality of their lending activity. Our sample begins with the 330 institutions responding to the survey conducted by Analytic Focus. Our analysis of the quantity of lending is limited to the 1993-2005 period, since 1993 is the first year that small business lending data was collected by bank regulators, and 2005 is the year of the survey. Our analysis of the quality of our sample banks' C&I loan portfolios is further constrained to the 2001-2005 time frame because data on nonperforming loans used in the quality regressions was not broken out by loan category on a consistent basis prior to 2001.[7]

For both the quantity and quality analyses, we eliminate banks with total assets exceeding $1 billion as of the June 2004 Call Report. We also drop institutions with thrift and/or

[7] Prior to 2001, there were three different Call Reports for banks with domestic offices only: banks with fewer than $100 million in total assets; banks with between $100 million and $300 million in total assets; and those with more than $300 million in total assets. For the first two categories, loan performance information for "commercial and industrial loans" was combined with that for "all other loans".

cooperative bank charters during the respective sample periods, as well as bank-year observations without commercial loans. Finally, we drop commercial banks that report having adopted credit scoring, but not indicating the year of adoption. This leaves us with a baseline sample of 3,089 observations on 278 community banks in our quantity analysis and 1,292 observations on these same banks in our quality analysis.

Our regression analyses of the quantity and quality of small business lending take the general form:

$$Y_{it} = \beta_1 \; SCOREVARS_{it} + \beta_2 \, BANKVARS_{it-1} + \beta_3 \, MKTVARS_{it} + \gamma_t + \varepsilon_{it} \quad (1)$$

where the dependent variable Y represents measures of the quantity and quality of lending. Specifically, we examine variation in: (1) the natural logarithm of the dollar amount of C&I loans with original amounts[8] of up to \$100,000 (*lnQLOANS≤100K*), and (2) the ratio of nonperforming (past due 90 days or more or nonaccrual) C&I loans to total loans (*C&I NPLRATIO*). The data for each dependent variable is for June 30 of year t, since the small business lending data are only available on the June Call Reports. All regressions are estimated using OLS.

The key exogenous variables in equation (1) – *SCOREVARS* – relate to the use of credit scoring by community banks. Observations for the year of adoption are omitted in order to reduce the likelihood of endogeneity and allow for adjustment to the new technology. The first credit scoring variable is simply an indicator of whether the bank reported using credit scores (CCS, SBCS, or both) for underwriting small business loans during year t *(SCORE)*. The second variable captures the number of years that the bank has been using credit scores as of year t (*YEARS SINCE*). The third credit scoring variable indicates whether the bank reports using credit scores to automatically accept/reject loan

[8] The original amount of a loan is the maximum of the loan amount and the amount of the line of credit or commitment, if any. For loan participations and syndications, the original amount refers to the entire amount of credit originated by the lead lender.

applicants (*AUTOACCEPT*). The fourth and final credit scoring variable indicates whether the bank reported using business credit scores (*BUSINESS SCORE*). The coefficients for the four credit scoring variables measure the effects, if any, of the technology on the quantity and quality of small business lending.

Note that *SCOREVARS* are constructed such that the bank is counted as using credit scoring technology if it uses the technology either for loans under $50,000 or for loans between $50,000 and $100,000.[9] The reason for this is that the survey data made a distinction between loans under $50,000 and loans between $50,000 and $100,000, while the Call Report only includes information about loans with original amounts up to $100,000.

Control variables for each bank (*BANKVARS*) are constructed for bank size, age, and financial condition. These are each measured as of December of the prior year – i.e., they are lagged by 6 months – in order to reduce concerns about endogeneity. Specifically, we include the natural logarithm of bank gross total assets (*LogGTA*), the natural logarithm of bank age (*LogAGE*), and the ratio of bank total equity to bank gross total assets (*EQUITYRATIO*).

Control variables for each banks' contemporaneous operating environment (MKTVARS) are also constructed that measure the degree of local competition and market conditions. Since many of the sample banks operate in more than one market – defined as either a rural county or metropolitan statistical area, or MSA – each variable is weighted across markets in which the bank operates by the bank's total deposits.[10] The specific variables that we include are the Herfindahl-Hirschman Index (HHI) based on deposits, the proportion of bank deposits controlled by large institutions with greater than $1 billion in total assets (LGPROP), the proportion of the bank's deposit activity in urban areas (MSAPROP), local area income one-year growth (INCOMEGR), and local area unemployment rate (UNEMPLOY). We also include an indicator if the bank responded on the Call Report that all or substantially all of the dollar value of its commercial and industrial loan portfolio had original amounts of $100,000

[9] All banks that report using credit scoring for loans between $50,000 and $100,000 also report using the technology for loans under $50,000.

[10] We use deposit markets (and weighting) instead of loan markets because deposits is the only variable on which we have bank branch-level data.

or less (*ONLY≤100K*).[11] In these cases, the dollar value of C&I loans was used as a proxy for *QLOANS* since these institutions did not complete Schedule RC-C Part II "Loans to Small Businesses and Small Farms" on the Call Report. We also include annual fixed effects (γ_t) in our regressions to account for temporal variation.

Table 4 provides the means and standard deviations of the variables used in our regressions. The statistics are for the 1993 to 2005 period, except that *C&I NPLRATIO* is measured only for 2001-2005. Across community banks and time, the average dollar volume of small business lending with original amounts less than or equal to $100,000 was only $5.4 million. The average commercial and industrial nonperforming loan ratio was 1.61%, based only on the 2001-2005 timeframe. As shown by the 25%, 50%, and 75% points in the distributions, both of these variables are skewed to the right. This is especially true for nonperforming loans, which has a median of only 0.37% but a mean of 1.61%.

In terms of the credit scoring variables, 23% of the observations are associated with the use of scores, but only 4% of the observations are associated with automated underwriting and 2% with business scoring technology, or SBCS.[12] The average number of years using credit scores was just over one year across the entire sample (inclusive of zeros for non-scorers) and about five years conditional on the bank using credit scores. These facts suggest that community banks use credit scores as a supplement to their normal underwriting; tend to primarily focus on consumer scores (CCS); and have been doing these things for several years.

Control variables for bank size, health, and age all seem consistent with the sample under study. The average community bank has about $135 million in gross total assets, an equity capital ratio of about 10.6%, and has been in existence for 66 years. Notably, 26% of the bank-year observations indicate that all or substantially all of the dollar value of its commercial and industrial loan portfolio had original amounts of $100,000 or less.

The market control variables for banking concentration, the proportion of deposits

[11] This is Call Report item RCON 6999.

[12] Note that while 23% of the observations are associated with credit scoring over the 1993-2005 period, some 46% of the institutions report using credit scores at the end of the sample.

controlled by large banking organizations, the proportion of deposits held in urban areas, income growth, and unemployment are also in line with expectations. On average, the markets within which the sample community banks operate are moderately concentrated (HHI = 0.2114) and have a significant representation by large banking organizations (42%). About half of the sample community banks' activity is conducted in metropolitan areas. The markets also saw average income growth of 1.9% and average unemployment of 4.7%.

IV. Results

Tables 5 and 6 present our regression results examining the effects of credit scoring on the quantity and quality of small business lending at community banks, respectively. The OLS regression represented by equation (1) is estimated for both of our dependent variables, the dollar value of lending and the nonperforming C&I loan ratio, with four individual specifications. The four specifications include different *SCOREVARS* in order to better understand whether and how the use of credit scoring affects the quantity and quality of lending.

Table 5 presents the results for regressions examining variation in the dollar value of commercial lending with original amounts of $100,000 or less at community banks. In column (1), we see that the use of credit scoring is positively related to the quantity of lending. The statistically significant coefficient of 0.0881 suggests that, all else equal, credit scoring is associated with about a nine percentage point increase in the quantity of small loans, given that the dependent variable is measured in natural log form. This is an economically significant amount. At the sample mean value of *QLOANS* of about $5.4 million, this would imply an increase in very small loans of about half a million dollars from the adoption of credit scoring to about $5.9 million.

The results presented in columns (2) - (4) suggest that this increase is driven by learning to use the technology over time. In particular, the dollar value of lending is estimated to increase by about 2.8% each year after adoption. In terms of the remaining *SCOREVARS*, the use of credit scores to automatically approve/reject loan applicants is generally negative, suggesting that banks using the technology in this way do not significantly increase their lending. Similarly, banks that use business scores do not appear to increase their lending. Thus, the increase in lending appears to primarily occur for banks that use CCS only and use it to supplement other lending technologies.

We also ran an additional set of quantity regressions that are not shown in Table 5 that substituted the natural log of the number of small C&I loans, rather than the dollar value of these loans. The results are generally consistent with those in Table 5 – the number of loans is about nine percentage points higher for scoring banks than non-scorers, all else equal, and the banks appear to ride a learning curve in using credit scoring technology.

Table 6 displays the results for our investigation of variation in nonperforming commercial and industrial loans. The data suggest a very weak statistical and economic relationship between credit scoring and loan quality. In column (1), the effect of *SCORE* on nonperforming loans is small and statistically insignificant. In columns (2) – (4), by contrast, some statistical relations are uncovered. The coefficient on YEARS SINCE in each case is positive and statistically significant, suggesting that credit quality may decline over time for scoring banks. But the use of credit scoring to automatically approve/reject loan applications and the use of business credit scores are both negative – statistically significant in the case of automatic decisions – suggesting credit quality improvements. Importantly, the R-Squared in each of these regressions is very low (around 0.04) and the estimates for the *SCOREVARS* are each economically very small. For example, in column (2), although the coefficient on *YEARS SINCE* is positive and significant, the coefficient on *SCORE* is negative and about three times as large in magnitude, suggesting that it would take three years after credit scoring adoption for credit scoring to have a weakening effect on credit quality. Thus, the use of credit scoring as it is typically done by community banks – using consumer credit scores only – is not associated with a discernable change in loan quality.

Our results suggest the following. First, the use of credit scoring by community banks is associated with a larger dollar value and number of small credits made to small businesses. Moreover, these institutions appear to be riding a learning curve as this increased lending is observed gradually over time. This increase may be confined to community banks that use consumer credit scores to supplement other lending technologies – i.e., it may not occur for the minorities of community banks that use business scores and that use automatic acceptance/rejection rules. Second, the use of credit scoring is not strongly associated with a change in the quality of community bank's C&I loan portfolio. Taken together, the results suggest that community banks that use consumer credit scores to supplement other lending technologies – which constitute the majority of community banks that use credit scoring technology – are able to increase their small business lending without suffering a material decrease in the quality of their portfolio. Community banks that use credit scoring to automatically accept or reject applicants or that use business scores may not increase their lending.

V. Conclusions

In recent years, a great deal of research attention has been paid to small business credit availability. Small firms have historically faced difficulties in raising funds due to a lack of credible information about them. Banks use several lending technologies to help them pierce this veil of informational opacity, including credit scoring. The research to date on the use of credit scoring in small business lending has focused on the use of small business credit scoring (SBCS) by the very largest banks, and has been based on a single 1998 survey.

This paper expands the research in several dimensions using the results of a new 2005 survey in which most of the respondents are community banks. The new survey evidence provides us with several surprising stylized facts about community banks and the credit scoring of small business loans. Community banks use credit scores in small business lending to a much larger extent than expected and have been using the technology for a number of years. Moreover, these institutions tend to use consumer credit scoring (CCS) when underwriting small business credits, rather than small business credit scoring (SBCS), and often use the scores for only very small loans (under $50,000). Community banks also do not typically use credit scores for automatic approval/rejection of loan applicants, suggesting that these institutions continue to stress relationship lending or other lending technologies.

Our empirical analysis suggests that the use by community banks of consumer credit scoring (CCS) to supplement other lending technologies – the way that most community banks use credit scoring technology – is associated with an increase in small business lending without any significant change in the quality of the banks' C&I loan portfolio. The increase in lending is observed gradually over time, suggesting that community banks ride a learning curve in determining how best to apply this technology. For the minorities of community banks that use credit scoring to automatically accept/reject loan applications or use SBCS, there does not appear to be a significant increase in lending.

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Table 1
Credit Scoring Survey Responses Delineated by Bank Size (Assets), Type of Credit Scores Used, and Loan Size

Panel A: Loans < $50,000

Bank Size Category	Consumer Scores Only (CCS)	Business Scores Only (SBCS)	Consumer & Business Scores (CCS & SBCS)	No Credit Scores	Total
Under $100 Million	51	1	4	68	124
$100 - $500M	49	1	6	73	129
$500M-$1Billion	18	1	7	20	46
Over $1 Billion	9	1	8	13	31
Total	127	4	25	174	330

Panel B: Loans between $50,000 - $100,000

Bank Size Category	Consumer Scores Only (CCS)	Business Scores Only (SBCS)	Consumer & Business Scores (CCS & SBCS)	No Credit Scores	Total
Under $100 Million	41	1	3	79	124
$100 - $500M	37	1	5	86	129
$500M-$1Billion	17	1	7	21	46
Over $1 Billion	7	1	7	16	31
Total	101	4	22	203	330

Panel C: Loans between $100,000 and $250,000

Bank Size Category	Consumer Scores Only (CCS)	Business Scores Only (SBCS)	Consumer & Business Scores (CCS & SBCS)	No Credit Scores	Total
Under $100 Million	41	1	3	79	124
$100 - $500M	37	1	4	87	129
$500M-$1Billion	17	1	6	22	46
Over $1 Billion	7	1	7	16	31
Total	101	4	20	205	330

Panel D: Loans > $250,000

Bank Size Category	Consumer Scores Only (CCS)	Business Scores Only (SBCS)	Consumer & Business Scores (CCS & SBCS)	No Credit Scores	Total
Under $100 Million	39	1	3	81	124
$100 - $500M	36	1	4	88	129
$500M-$1Billion	15	0	5	26	46
Over $1 Billion	7	1	7	16	31
Total	97	3	19	211	330

Table 2
Adoption of Credit Scoring for Small Business Lending by Community Banks
(≤$1 Billion in Total Assets)

Time	Consumer Scores Only (CCS)	Business Scores Only (SBCS)	Both Consumer and Business Scores (CCS & SBCS)	Total
1994 or Prior	16	0	2	18
1995	11	0	1	12
1996	8	0	1	9
1997	6	0	1	7
1998	8	1	1	10
1999	7	0	1	8
2000	8	0	1	9
2001	11	0	0	11
2002	12	1	0	13
2003	8	0	2	10
2004	8	0	4	12
2005	5	1	2	8
Total	108	3	16	127*

* There were 138 community banks that responded using some form of credit scoring for their small business loans. However, only 127 of these institutions responded to the survey question related to the date of adoption.

Table 3
Number of Banks Using Credit Scores
Auto Decision Banks (use scores to automatically accept/reject) vs. Supplementing Banks (all other banks)
Sorted by Loan Size and Bank Size

Panel A: Auto Decision Banks: Loan Size versus Bank Size

	Loan Size			
Bank Size	< $50,000	$50,000 - $100,000	$100,000-$250,000	Over $250,000
Under $100 Million	12	4	4	4
$100 - $500M	11	2	2	2
$500M-$1Billion	6	2	0	0
Total	29	8	6	6

Panel B: Supplementing Banks: Loan Size versus Bank Size

	Loan Size			
Bank Size	< $50,000	$50,000 - $100,000	$100,000-$250,000	Over $250,000
Under $100 Million	56	45	45	43
$100 - $500M	56	43	42	41
$500M-$1Billion	26	25	24	20
Total	138	112	111	104

Table 4							
Variables & Summary Statistics							
Means, standard deviations, and percentiles for variables used in subsequent estimation. The sample combines loan observations from 278 community banks (gross total assets ≤ $1 billion) responding to the credit scoring survey. Loan observations for the year of credit scoring adoption are excluded. (Description of variables.) The total sample size is 3,089 bank-year observations for the 1993 to 2005 period. (*C&I NPLRATIO* is measured only between 2001 and 2005, resulting in only 1,292 observations.) Sources: Analytic Focus 2005 Credit Scoring Survey and commercial bank regulatory reports (Call Reports, Summary of Deposits, National Information Center).							
Variable	Description	Mean	Std Dev	25%	50%	75%	Nobs
Dependent Variables:							
QLOANS (0-100K) ($000)	Total C&I lending with original amounts ≤ $100,000 ($000)	5,439.22	6,119.41	1,731.00	3,474.00	6,772.00	3,089
C&I NPLRATIO	Nonperforming and nonaccrual C&I loans ÷ Total C&I loans	0.0161	0.0390	0.0000	0.0037	0.0155	1,292
Credit Scoring Variables:							
SCORE	Bank uses credit scoring (1=yes)	0.2279	0.4195	0.0000	0.0000	0.0000	3,089
YEARS SINCE	Number of years since the bank started using credit scoring	1.1392	2.5633	0.0000	0.0000	0.0000	3,089
AUTOACCEPT	Dummy indicating that the bank uses credit scores to automatically approve or reject loan applications	0.0447	0.2066	0.0000	0.0000	0.0000	3,089
BUSINESS SCORE	Dummy indicating that the bank uses small business credit scores	0.0188	0.1358	0.0000	0.0000	0.0000	3,089
Bank Variables:							
GTA ($000)	Gross total assets ($000)	134,813.94	146,386.39	41,729.00	77,963.00	167,840.00	3,089
EQUITYRATIO	Total equity ÷ GTA	0.1060	0.0561	0.0806	0.0940	0.1162	3,089
AGE	Age of the bank (years)	65.56	39.89	23.97	76.05	96.99	3,089
ONLY 0-100K	Dummy indicating whether all or substantially all of the bank's C&I loans have original amounts ≤ $100,000	0.2648	0.4413	0.0000	0.0000	1.0000	3,089
Market Variables:							
HHI	Herfindahl-Hirschman Index in markets served by the bank (weighted across markets by the bank's total deposits)	0.2114	0.1,183	0.1319	0.1809	0.2517	3,089
LGPROP	Proportion of deposits controlled by large banks in markets served by the bank (weighted across markets by the banks total deposits)	0.4183	0.3105	0.1186	0.4195	0.6858	3,089
MSAPROP	Proportion of the bank's total deposits booked in MSA markets.	0.4927	0.4774	0.00	0.4412	1.0000	3,089
INCOMEGR	Average income growth in markets served by bank (weighted across markets by the bank's total deposits)	0.0190	0.0417	0.0002	0.0177	0.0353	3,089
UNEMPLOY	Average unemployment rate in markets served by bank (weighted across markets by the bank's total deposits)	0.0471	0.0173	0.0349	0.0441	0.0559	3,089

Table 5

Quantity Regressions: Dollar Value of Loans of $100,000 or Less

OLS Regressions for *lnQLOANS (0-100K)*, or the natural logarithm of one plus the dollar value of small business loans with original amounts in the $0-$100K range reported by bank *i* on the June Call Report for year *t*. For banks reporting that "all or substantially all of their C&I loan portfolios had original amounts of $100,000 or less," the total dollar value of C&I loans is used. The variable *ONLY 0-100K* indicates these observations. The sample uses observations for 278 community banks (gross total assets ≤ $1 billion) responding to the credit scoring survey. Loan observations for the year of credit scoring adoption are excluded. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. t statistics are in parentheses.

	(1)	(2)	(3)	(4)
Credit Scoring Variables:				
SCORE	0.0881***	-0.0447	-0.0262	-0.0105
	(2.502)	(-0.747)	(-0.427)	(-0.168)
YEARS SINCE		0.0276***	0.0279***	0.0272***
		(2.743)	(2.778)	(2.696)
AUTOACCEPT			-0.1021	-0.1019
			(-1.361)	(-1.359)
BUSINESS SCORE				-0.1526
				(-1.401)
Bank Variables:				
ln(GTA)	0.8899***	0.8891***	0.8890***	0.8895***
	(52.33)	(52.33)	(52.33)	(52.36)
EQUITYRATIO	-1.1938***	-1.1509***	-1.1450***	-1.1372***
	(-4.421)	(-4.259)	(-4.237)	(-4.208)
ln(Age)	-0.1229***	-0.1282***	-0.1282***	-0.1292***
	(-8.676)	(-8.977)	(-8.979)	(-9.036)
ONLY 0-100K	0.5836***	0.5837***	0.5813***	0.5804***
	(15.41)	(15.42)	(15.35)	(15.33)
Market Variables:				
HHI	0.0505	0.0402	0.0539	0.0750
	(0.364)	(0.290)	(0.388)	(0.537)
LGPROP	-0.2254***	-0.2217***	-0.2180***	-0.2190***
	(-3.028)	(-2.982)	(-2.930)	(-2.945)
MSAPROP	-0.0174	-0.0197	-0.0220	-0.0185
	(-0.362)	(-0.409)	(-0.456)	(-0.383)
INCOMEGR	0.0624	0.0909	0.1026	0.1176
	(0.169)	(0.246)	(0.278)	(0.319)
UNEMPLOY	-3.4087***	-3.4230***	-3.4670***	-3.4537***
	(-3.758)	(-3.779)	(-3.825)	(-3.810)
Constant	-1.2460***	-1.2086***	-1.2064***	-1.2168***
	(-6.060)	(-5.871)	(-5.861)	(-5.909)
Time fixed effects	Yes	Yes	Yes	Yes
R-Squared	0.5116	0.5128	0.5131	0.5134
Number of observations	3,089	3,089	3,089	3,089

Table 6

Quality Regressions: Ratio of Nonperforming C&I Loans to Total C&I Loans

OLS regressions for *C&I NPLRATIO*, or the ratio of the dollar amount of commercial and industrial loans more than 90 days past due or in nonaccrual status to the total dollar amount of commercial and industrial loans outstanding reported by bank *i* on the June Call Report for year *t*. The sample uses observations for 278 community banks (gross total assets ≤ $1 billion) responding to the credit scoring survey. Loan observations for the year of credit scoring adoption are excluded. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. t statistics are in parentheses.

	(1)	(2)	(3)	(4)
Credit Scoring Variables:				
SCORE	0.0027	-0.0059	-0.0047	-0.0039
	(1.178)	(-1.427)	(-1.119)	(-0.895)
YEARS SINCE		0.0014**	0.0015**	0.0014**
		(2.469)	(2.540)	(2.452)
AUTOACCEPT			-0.0078*	-0.0080*
			(-1.674)	(-1.707)
BUSINESS SCORE				-0.0063
				(-0.978)
Bank Variables:				
ln(GTA)	-0.0032***	-0.0033***	-0.0034***	-0.0033***
	(-2.657)	(-2.746)	(-2.821)	(-2.759)
EQUITYRATIO	-0.0176	-0.0149	-0.0143	-0.0145
	(-0.919)	(-0.780)	(-1.050)	(-0.756)
ln(Age)	0.0015	0.0011	0.0011	-0.0010
	(1.536)	(1.011)	(1.050)	(0.989)
Market Variables:				
HHI	0.0355***	0.0340***	0.0347***	0.0361***
	(3.297)	(3.161)	(3.222)	(3.326)
LGPROP	-0.0144**	-0.0142**	-0.0140**	-0.0140**
	(-2.422)	(-2.400)	(-2.364)	(-2.367)
MSAPROP	0.0043	0.0041	0.0040	0.0042
	(1.120)	(1.074)	(1.051)	(1.100)
INCOMEGR	0.0100	0.0130	0.0140	0.0148
	(0.327)	(0.425)	(0.459)	(0.484)
UNEMPLOY	0.0844	0.0890	0.0813	0.0784
	(1.048)	(1.107)	(1.011)	(0.974)
Constant	0.0411***	0.0440***	0.0453***	0.0445***
	(2.798)	(2.988)	(3.076)	(3.014)
Time fixed effects	Yes	Yes	Yes	Yes
R-Squared	0.0386	0.0431	0.0452	0.0460
Number of observations	1,292	1,292	1,292	1,292