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Abstract: We test whether rural versus urban location, and the amount of social capital present in those locations, influence the performance of Small Business Administration (SBA) 7(a) loans originated between 1984 and 2012. On average, we find that rural loans are about 11% less likely to default than urban loans, and that a standard deviation increase in social capital reduces default by about 5%. Surprisingly, these two effects are largely independent of each other, even though social capital is substantially higher in rural places than in urban places. Our findings advance the small business lending literature and offer insights for a more efficient allocation of SBA funds.

Keywords: Commercial banks; Rural lending; Small business loans; Social capital

1. Introduction

Commercial banks play a central role in providing credit to opaque small businesses. By fostering close relationships with small businesses, banks can transcend the information asymmetries that prevent these firms from accessing capital markets. These information problems are especially problematic for new businesses, as well as for mature small businesses that have blemished credit records. Lending to these firms can expose banks to substantial credit risk; banks that do so need to be expert at evaluating the creditworthiness of these borrowers.

It is an article of faith among many that small, so-called community banks are better at this task than large banks. Community bank advocates argue that in-person customer relationships develop more naturally at these locally-focused banks, and through these relationships banks can collect the soft (non-quantifiable) information needed to assess whether or not small businesses are creditworthy.[1] Academic research offers support for this view. Cole, Goldberg and White (2004) find that large U.S. banks (assets greater than $1 billion) rely more on hard information embedded in borrower financial statements when screening credit applications from small businesses, while smaller banks rely more on soft information about the character of the borrower. Similarly, Berger, et al. (2005) conclude that small banks are better able to collect and act on soft information and tend to lend to more difficult credits, while large banks lend on a more impersonal basis and have shorter and less exclusive lending relationships. And Berger, Cowan and Frame (2011) find that even when small banks do use hard information to assess the creditworthiness of small business firms, they tend to use the consumer credit score of the business owner, not the more encompassing small business credit score used by large banks.[2]

The advantages associated with relationship-based lending are likely to be more pronounced in rural places, where personal relationships are an integral part of the social fabric. If one accepts the conventional wisdom that rural communities are closer knit than urban communities—i.e., they are places where "everyone knows each other's business"—then this information grapevine will include the business community. This will provide rural banks with a relatively low-cost endowment of soft information about

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[1] The head of a community banking trade association has expressed it this way: "Because most community banks are locally owned and operated, they have strong ties to their local communities. These banks have a close relationship with their customers and are quite familiar with their customers' financial condition and their history and ability to repay (ICBA 2011)." Two Federal Reserve economists have expressed it this way: "Community bankers typically know their customers better than bankers at larger organizations, and perhaps this knowledge of local people and local businesses offsets the exposure to local economic downturns. As a consequence, community banks seem to hang tight through the choppy waters of local economic downturns (Hall and Yeager 2002)."

[2] More recent research provides indirect evidence that bank size is inversely related to relationship-based, soft information lending. Ogura and Uchida (2017) found that soft information acquisition declines after small bank mergers, but not after large bank mergers. Cole (2017) shows that the decline in small business lending during the financial crisis was significantly greater at large banks than at small banks.

local businesses, over and above what is available to urban banks. If the quality and quantity of this soft information advantage are large enough, rural lenders will be especially effective at loan screening and monitoring, resulting in a lower probability of small business loan default. Perhaps just as important, the rural information grapevine may also transmit information about loan performance in the opposite direction, from the bank to the community. To the extent that wider knowledge of loan default equates with a higher expected level of (psychically costly) community shame for the defaulting local businessperson, moral hazard incentives will be weaker and rural borrowers will work harder to avoid loan default.

Our conjecture that rural banks may have competitive advantages in small business lending is based on more than just the social and civic underpinnings of rural commerce, the soft information that these communities generate, and the borrower behaviors that these circumstances may engender. In general, small businesses tend to be hard information-deficient, and this should be even more likely for rural firms than for urban firms. Allee and Yohn (2009) found that a firm's size positively predicts whether its financial statements are compiled, reviewed or audited by a professional accounting firm. Given the smaller size of rural firms, this would mean that loan applications from rural firms are less likely to supported by audited financial statements. Similarly, in small rural economies the re-sale market for fixed investments and specialized assets will be relatively thin, making it difficult for lenders to assess the losses given default associated with pledged collateral. Finally, Berger and Udell (2002) argue that agency conflicts between bank shareholders and loan officers (the traditional repository of soft information) are more easily mitigated at small banks in small places. At such banks, managers are likely to have extensive personal knowledge of most business borrowers and participate in making and reviewing most business lending decisions. Moreover, ownership concentration tends to be high at these banks and top managers are likely to be drawn from among that ownership, resulting in better corporate governance and hence better loan portfolio performance (Spong and Sullivan 2007).

We provide empirical evidence consistent with these notions. Our data are a random sample of 33,945 loans to small U.S. businesses made by 6,045 different community banks between 1984 and 2012, under the auspices of the Small Business Administration flagship 7(a) loan program. For each of these loans, we classify the borrowing firm as either rural or urban based on whether it is located within or outside of an MSA, and we classify the lending bank as either rural or urban based on whether the bank office making the loan is located within or outside of an MSA. Using a discrete-time hazard model of loan default, we find that purely rural loans (i.e., loans in which both the borrower and the lender are located in rural places) are statistically and economically less likely to default than purely urban loans; this result suggests the existence of some undefined characteristic that we call *ruralness*.

We perform additional tests to identify the dimensions of this ruralness loan performance advantage. First, for very small community banks (assets less than $250 million in 2000 dollars), we show that ruralness is a joint product of rural banks lending to rural borrowers. At these very small banks, purely rural loans are statistically and economically less likely to default than loans in which either the borrower or the lender (but not both) is rural. This suggests that a *shared rural culture* is an important component of ruralness for very small banks, although we do not find this result for loans made by larger community banks. Second, we show that ruralness is not necessarily a neighborhood effect. Holding the geographic distance (in miles) between borrowers and lenders constant, loans between counterparties located in different rural counties are no more likely to default than loans between counterparties located in the same rural county. Thus, *localness* is not a necessary condition for ruralness, which suggests that ruralness is geographically portable. Interestingly, we show that localness does matter for urban small business lending: Loans between urban counterparties located in the same MSA are statistically and economically less likely to default than loans between urban counterparties located in different MSAs. Third, we show that the ruralness effects in our data are distinct from *social capital* effects. According to Putnam (2000) and others, social capital is the set of interpersonal networks within a community—examples include civic organizations, sports leagues, religious groups, non-profit associations, and voter participation in elections—and the norms of reciprocity and trustworthiness that arise from those networks. We show that small business loans are statistically and economically less likely to default in both rural places and in urban places where quantitative indicators of per capita social capital are high. But even though (and perhaps not surprisingly) rural markets have higher average levels of social capital per person than urban markets in our data, adding social capital regressors to our models leaves the ruralness result statistically and economically intact. That is, ruralness exists alongside, but is not caused by, high levels of social capital.

Our results suggest the existence of informational and behavioral efficiencies in rural lending markets that are less present in urban lending markets. As such, rural banks more closely match the classical description of a local bank as a repository of private local information that allows it to outperform both non-banks and non-local banks in the analysis of local creditworthiness. Although the number of small banks in the U.S. has declined precipitously since the 1980s, rural banks continue to have a disproportionate presence: About 48% of all community banks are located in rural or micropolitan areas, places that account for only about 16% of the U.S. population.[3] But these banks also tend to operate well below what most banking economists would consider to be efficient scale: In 2017, the median rural bank held only $147 million in

[3] Percentages calculated using data from Anderlik and Coffer (2014) and U.S. Census Bureau (2012), respectively. A micropolitan area is a county or group of contiguous counties that are clustered around a central city with a population of less than 50,000.

assets and three-quarters of all rural banks held less than $300 million in assets.[4] If the rural lending efficiencies we find here prove to be robust to ongoing technological change, then the independent small-town banking business model may continue to be viable in the future.[5] The arithmetic is straightforward: Holding information technology constant, rural lending efficiencies plus the rents potentially available in oligopolistic small-town banking markets would need to exceed the production inefficiencies from operating at suboptimal scale. Gilbert and Wheelock (2013) provide some suggestive evidence regarding this calculus, by showing that small banks maintained their shares of local deposits in rural counties between 2001 and 2012 relative to large banks with branches located in those markets.

There is a large literature on the importance of small business lending to the macro-economy, the scope and evolution of small business lending technologies, and the performance of small business loans and the banks that make those loans. Berger (2015) and Udell (2015) provide the most recent surveys of this literature. Only a small handful of studies address these issues in the context of rural banks, and the results of those studies are consistent with our discussion here. Brickley, Linck and Smith (2003) showed that the office, ownership, and management structure of banks varies systematically across different markets and customer bases; they found that rural banks are more likely to be locally controlled, due to the advantages such banks may have in knowing customers and making decisions locally. Cowan (2006) found that rural banks are less likely to use credit scoring for small business loans than comparable urban banks. Kittiakarasakun (2010) concluded that urban banks tend to rely more on verifiable hard information while rural banks tend to lend to nearby customers about which they have personal knowledge. We extend this literature by comparing the default probabilities of small business loans made by small rural banks and urban banks, in tests designed to reveal how the informational environments in these markets influence loan performance.

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[4] Using relatively standard econometric cost function analyses, both McAllister and McManus (1993) and Wheelock and Wilson (2001) found increasing returns to scale for U.S. commercial banks with less than $500 million in assets. Estimates from more recent studies that use alternative methodologies are consistent with these findings (DeYoung 2013, Chiorazzo, D'Apice, DeYoung, and Morelli 2018). While further unit cost reductions exist as community banks grow larger than $500 million, the rate at which unit costs decline apparently slows. In contrast, research suggests that scale economies may be unlimited for large banks that use high-volume production models that very different from community bank technology (e.g., Wheelock and Wilson 2012, Hughes and Mester 2013).

[5] With continued improvements in information technology, lenders have become increasingly able to lend fully or partially based on hard information. See Berger and Udell (1995, 2006), Petersen and Rajan (2002), DeYoung, Frame, Glennon and Nigro (2010), Berger and Black (2011), Udell (2015), and Jagtiani and Lemieux (2016, 2018).

2. Hypotheses

The aim of this study is to generate evidence useful for addressing the following broad question: How and why does the performance of small business loans made by small rural banks and small urban banks differ? To answer this (and related) questions, we compare and contrast the default rates for loans made by rural and urban community banks to rural and urban small businesses.

It is natural to use default rates to draw inferences about the existence of lending relationships. A true borrower-lender relationship generates soft information about the borrower's creditworthiness that a bank can use to construct a sustainable lending strategy that reduces the likelihood of borrower default. Just as important, lenders should be willing to incur short-term costs to develop and preserve a valuable long-term lending relationship, and hence will be more likely to restructure a troubled loan rather than calling that loan and forcing default.

We posit and test four inter-related hypotheses in which the characteristics of agents (firms versus banks), types of agents (urban versus rural), agent locations (local versus non-local), and civic conditions (amount of social capital) predict the probability of loan default. We state each of these hypotheses in a neutral fashion, so that each hypothesis supports a two-sided test that treats rural loans and urban loans symmetrically. Let D(x) represent the probability that a loan will default, where x indicates locational information about the borrowing firm and the lending bank as follows:

x = RR indicates a rural firm borrowing from a rural bank
x = UU indicates an urban firm borrowing from an urban bank
x = RU indicates a rural firm borrowing from an urban bank
x = UR indicates an urban firm borrowing from a rural bank

This four-way taxonomy of borrower-lender pairs is exhaustive and mutually exclusive. We use this taxonomy to state our first two hypotheses.

H1. Ruralness Hypothesis: The efficiency of loan contracting and monitoring in rural markets will differ from that in urban markets, due to differences in informational, institutional and/or cultural conditions in those markets.

Using the notation introduced above, D(RR) < D(UU) is consistent with the existence of ruralness effects that make loan contracting and monitoring more efficient. This finding would imply that relevant information on borrower creditworthiness is more available, this information is less costly to acquire, and/or borrower-lender relationships are stronger in rural markets than in urban markets.[6] Similarly, D(RR) > D(UU) is consistent with the existence of ruralness effects that *reduce* the efficiency of loan contracting and monitoring.

Should our tests produce evidence consistent with the existence of ruralness, we will of course be interested in the source(s) of this ruralness. Our second hypothesis examines whether ruralness depends on the borrower and lender sharing the same culture.

H2. Shared Culture Hypothesis: Agents of the same type—that is, urban banks paired with urban firms, or rural banks paired with rural firms—share informational, institutional and/or cultural similarities that make loan contracting and monitoring more efficient.

All else equal, both D(RR) < D(RU) and D(RR) < D(UR) are consistent with shared rural culture, while D(UU) < D(RU) and D(UU) < D(UR) are consistent with shared urban culture. These two outcomes are not mutually exclusive; shared culture effects can exist simultaneously in both rural credit markets and in urban credit markets.

Testing our next hypothesis requires the following more detailed taxonomy of the relative locations of borrower-lender pairs:

x = RRL indicates a rural firm borrowing from a local rural bank
x = RRNL indicates a rural firm borrowing from a non-local rural bank
x = UUL indicates an urban firm borrowing from a local urban bank
x = UUNL indicates an urban firm borrowing from a non-local urban bank
x = RU indicates a rural firm borrowing from an urban bank
x = UR indicates an urban firm borrowing from a rural bank

where "non-local" refers to a lender located in a city, town or county different from the borrower (details below). This six-way taxonomy reorganizes shared-culture loans (RR, UU) into two types: shared-culture local loans (RRL, UUL) and shared-culture non-local loans (RRNL, UUNL). As such, this taxonomy continues to be exhaustive and mutually exclusive. The finer detail permits us to examine whether ruralness depends on the borrower and lender being in close local proximity.

H3. Local Lending Hypothesis: Pairs of agents in the same local market have relatively low costs of information sharing and/or information revelation, making loan contracting and monitoring more efficient.

[6] Note that a lower default rate for relationship lending does not necessarily map into higher profitability. Numerous other facets of loan production—such as pricing, optimal scale, diversification effects, and ancillary revenues—differ across the relationship and non-relationship lending models and have important impacts on bank profitability.

All else equal, D(RRL) < D(RRNL) is consistent with local market lending efficiency effects in rural markets. Similarly, D(UUL) < D(UUNL) is consistent with local market lending efficiency effects in urban markets. These two outcomes are not mutually exclusive; local lending efficiency effects can exist simultaneously in both rural credit markets and in urban credit markets. While finding evidence of localness *per se* would not be surprising—for example, DeYoung, Glennon and Nigro (2008) found that localness, measured in terms of the geographic distance between borrowers and lenders, to be strongly and negatively related to loan default—this test may determine whether localness is relatively more important in rural or urban settings.

At a fundamental level, one would expect the behavior of agents in both rural and urban places to reflect, at least on average, the social customs and societal expectations present in those places. The network of interactions among the agents who live and work in a particular society, which in the end determines how well that society functions, has been referred to as the "social capital" of that society. As described by Guiso, Sapienza and Zingales (2004), social capital impacts economic efficiency "by enhancing the prevailing level of trust. In high-social-capital communities, people may trust each other more because the networks in their community provide better opportunities to punish deviants. At the same time, in these communities people may rely more on others' keeping their promises because of the moral attitude imprinted with education." The authors identify exogenous differences in social capital across 95 Italian provinces, and find that financial transactions that involve trust (e.g., accepting personal checks as payment, extending credit to households) are more likely to occur in provinces with more social capital. Clearly, a small business loan is a financial transaction that requires trust, and as such the performance of small business loans should reflect the level of social capital present where the small business borrower and/or her lender lives and works.

H4. Social Capital Hypothesis: High levels of social capital in the local market make loan contracting and monitoring more efficient.

All else equal, we expect to find D(high social capital) < D(low social capital) in both rural and urban markets. If we find this result in rural markets ***and*** we find that rural markets exhibit greater amounts of social capital than urban markets—as one might expect, given our casual observations regarding the close-knit nature of rural places—then we can conclude that social capital is an attribute of ruralness. Note that social capital effects can be thought of as distinct from soft information effects: A overall higher level of trust in a society encourages a high volume of small business lending; a greater amount of soft information in a society allows lenders to better determine which small businesses are and are not trustworthy.

2.1. Some identification issues

Testing some of the above hypotheses is potentially problematic, because a firm's decision to apply for a loan from its local bank, rather than from a bank outside its local market, is not exogenous. This decision can depend on (a) the firm's own default characteristics and/or (b) the default characteristics of the local bank's loan portfolio.

Let's examine (a) first. A borrower might leave the local market because she is known to be a bad credit risk and hence will be declined for credit by local lenders. The results from an exodus of low quality borrowers to out-of-market lenders is pooled with the predicted *local lending* result: D(RRL) < D(RRNL) and D(UUL) < D(UUNL). But this pooling causes no identification problem in competitive local markets (where, by the local lending hypothesis, lenders will on average decline credit to local borrowers only if they are indeed low quality) or in non-competitive local markets (where lenders that restrict output will be declining credit to high quality, not low quality, local borrowers). The results from an exodus of low quality borrowers to out-of-market lenders is also pooled with the predicted *shared culture* result: D(RR) < D(RU) and D(UU) < D(UR). This pooling could potentially cause identification difficulties. If we find that in-market borrowers (say, RR loans) perform better than out-of-market borrowers (RU loans), then we could not confidently conclude that this is evidence of shared culture effects. However, if we find that in-market borrowers perform worse than out-of-market borrowers, then we could confidently reject the shared culture hypothesis.

Now let's examine (b). Borrowers might have to go out-of-market if local banks have market power and constrain the availability of credit. This is most likely in rural markets, where the number of banks tends to be small. For example, assume that the marginal loan default rate in competitive local markets is 5%, but in monopoly local markets loan output is restricted and the marginal default rate is only 2%. Then the marginal borrower that leaves a local monopoly market will have a lower default rate (2%) than the marginal borrower in the non-local competitive market in which she ends up getting her loan (5%). Hence, if rural markets tend to exhibit less lending competition than urban markets, rural out-of-market borrowers will have lower default rates than urban out-of-market borrowers; that is, we would find D(RRNL) < D(UUNL) and/or D(RU) < D(UR). Fortunately, these outcomes are not pooled with any of the results predicted by our formal hypotheses.

Only a few studies have attempted to test whether rural borrowers face limited credit access. Walraven (1999), using data from the 1993 National Survey of Small Business Finance, found that rural small businesses were significantly less likely than urban small businesses to apply for a loan, and that rural small business loan applications were significantly more likely to be accepted than urban small business loan applications. Briggeman and Akers (2010), using data from both the 2005 Agricultural Resource Management Survey and the 2003 National Survey of Small Business Finance, concluded that rural small business owners reported having fewer problems in receiving credit than their urban counterparts. These findings are inconsistent with the notion that credit access in rural markets is restricted relative to urban markets.[7] Nevertheless, in our tests we control for the effects of market power on both in-market and out-of-market loan default rates.

3. Data

We test our hypotheses for 33,945 small business loans originated by small U.S. commercial banks between January 1984 and January 2012 under the Small Business Administration (SBA) flagship 7(a) loan program. The 7(a) loan program serves small business firms that are unable to access credit on reasonable terms without having a third-party guarantor, despite having sound prospects for repayment. Banks select the firms to receive loans, initiate SBA involvement, underwrite the loans within SBA program guidelines, provide 100% of the loan funding, and monitor and report back to the SBA the progress of these loans. All loans must be secured by the tangible assets of the firm, and each loan contract includes a loss sharing arrangement between the SBA and the bank lender: A fixed percentage guarantee is set at loan origination. In case of loan default, the lender receives an amount equal to the guarantee percentage multiplied by the remaining unpaid loan balance, but bears a loss on the remainder of the loan balance. The guarantee percentage varies idiosyncratically across loans made in any given year, and has increased and decreased over time depending on the budgetary resources made available to the SBA.

Our data come from a random sample of all SBA 7(a) loans with seven-year maturities originated during the 1984-2012 sample period, stratified to contain 20% of the loans originated in each year. The majority of loans in the SBA 7(a) portfolio have contractual maturities of seven years, and SBA loans with maturities shorter (three years) and longer (fifteen years) than seven years have been shown to exhibit different intertemporal default behaviors (Glennon and Nigro, 2005). From this initial random sample, we retain only the loans that were made by commercial banks with assets less than $1 billion (2000 dollars), consistent with our focus on the rural small business lending environment in which nearly all bank lenders are quite small.

Table 1 displays the number of loans in our data and the annual distribution of those loans. The number of loans varies substantially from year to year, predominantly due to annual variation in federal funding for SBA programs. Across the entire sample period, 31.7% of the loans in our data were received by rural borrowers (the small business was located outside of an MSA) and 27.1% of the loans in our data were made by rural lenders (the bank's lending office was located outside of an MSA). At

[7] By itself, the Walraven (1999) finding could indicate that limited credit access discouraged rural firms from applying for loans. But the Briggeman and Akers (2010) finding makes this possibility unlikely.

origination, the average loan had a principal balance of $180,000 and was made by a bank with $559 million in total assets (both in 2000 dollars).

3.1. Default rates on SBA loans

Default rates on SBA-guaranteed loans are high. About one-in-six loans (17.6%) of the loans in our data defaulted before the end of the sample period. However, despite this extraordinarily high default probability, expected losses on SBA loans are not much higher than expected losses on non-guaranteed small business loans. This is because the high SBA guarantee percentages, which averaged 78.6% across the loans in our data, places a floor under loan losses given default. By our rough calculations, expected loss rates are about 2.2% for SBA loans and between 0.8% and 1.3% for non-SBA small business loans.

Our rough calculations are displayed in Table 2. For SBA loans, the expected default frequency (EDF) of 17.6% comes directly from our data. We derive the 13.4% loss given default (LGD) figure for SBA as follows: We multiply a 21.4% exposure rate (i.e., 100% minus the 78.6% average SBA guarantee percentage from our data) by the contractual loan principal at end of each year, based on a seven-year loan amortization schedule at a 10.3% annual rate of interest (Glennon and Nigro, 2005), assume a uniform distribution for loan default over time, and calculate the discounted sum of these figures at an assumed 8% cost of capital. For non-SBA loans we calculate expected loss rates two ways. For Estimate A, we use the average 1.7% ratio of commercial and industrial (C&I) loans that are non-accruing or past due 90 days at U.S. commercial banks as a proxy for EDF, and Shibut and Singer's (2014) 57% average loss rate for small C&I loans at failed banks to measure LGD. Estimate B is simply the average aggregate net charge-off rates for C&I loans at banks with assets between $300 million and $1 billion over our sample period.[8]

These calculations imply that, despite the presence of generous third-party government loss guarantees, bank lenders put at least as much capital at risk when they make an SBA loan as when they make a non-SBA small business loan. Thus, exposure to credit loss provide SBA lenders with clear incentives to monitor and mitigate risk in this portion of their loan portfolios.

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[8] Shibut and Singer (2014) calculate the 57% LGD figure based on actual losses on individual C&I loans incurred by the FDIC during resolutions of small insolvent commercial banks. We calculate the 78% LGD figure based on the reasonable assumption that all of the C&I loans made by $300 million to $1 billion banks are small business loans. Other studies report somewhat lower LGD figures, but they base their calculations on loan data from very large banks. Asarnow and Edwards (1995) found a 35% LGD for commercial loans made by CitiBank, while Schuermann (2004) found a 35% LGD for commercial loans to large publicly rated firms.

3.2. Borrower-lender location and loan default rates

The SBA data include the state, city, county, street address, and zip code for each small business borrower and for each bank lending office (usually but not always the bank headquarters). We link the zip codes to the 1990, 2000 and 2010 U.S. Census databases to determine whether borrowers and lenders are in urban or rural markets. Borrowers and/or lenders located in a Metropolitan Statistical Areas (MSAs) are defined as urban, while borrowers or lenders located in non-MSA counties are defined as rural. We use these designations to assign each loan in our data to the four-way and six-way locational taxonomies defined above.

Table 3 shows the distribution of loans across the four-way (panel A) and six-way (panel B) locational taxonomies. Not surprisingly, pure urban loans (UU) account of the majority of the data set. About 62% of the loans are UU, while about 21% are pure rural loans (RR), with the remaining 17% having one foot in both types of places (RU or UR). Rural borrowers are located in different counties than their rural lenders (RRNL) in about 25% of the pure rural loans (1,774/7,056), while urban borrowers are located in different MSAs than their urban lenders (UUNL) in about 28% of the pure urban loans (5,866/21,072).

Table 3 also allows a first preliminary look at how default rates vary across geographic categories. The raw data are consistent with the ruralness hypothesis, with RR loans defaulting 200 basis points less often than UU loans. There is suggestive evidence that rural borrowers (as opposed to rural lenders) are the primary driver of the ruralness result: RU loans defaulted 300 basis points less often than UU loans and 230 basis points less often than UR loans. The raw data are also partially consistent with the local lending hypothesis for urban loans, as UUNL loans default 280 basis points more often than UUL loans.

3.3. Social capital and loan default rates

Knowing the geographic location of borrowers and lenders allows us to assign a social capital score to each borrower, each lender, and each loan. Researchers at the Northeast Regional Center for Rural Development (Penn State University) have calculated and posted online annual social capital indices for 1990, 1997, and 2006 for most counties in the U.S. These indices combine data on (a) the per capita number of civic, religious, political, professional, business, labor, and athletic organizations and associations in each county, (b) the per capita number of non-profit organizations and associations in each county, (c) the county response rate to the most recent mailed survey from the U.S. Census Bureau, and (d) the percentage of voting age county residents that voted in the most recent national election. Previous research has found or theorized links between indicators such as these and higher levels of trust and reciprocity in society and/or the marketplace (Putnam 2000; Guiso, Sapienza and Zingales 2004; Rupasingha, Goetz and Freshwater 2006). A social capital index is then formed by standardizing the cross-county distributions of each of the four items to have zero means and unit standard deviations, and then summing the four standardized items within each county. We assign the values of this standardized index to every loan in our data, using the annual index value (1990, 1997 or 2005) closest to the loan origination date. We then create three social capital variables for use in our tests: The social capital in the county of the small business borrower (*Borrower SocCap*), the social capital in the county of the bank lending office (*Lender SocCap*), and the average of the borrower and lender social capital (*Average SocCap*).

Table 3, panel C shows the distribution of loans and loan default rates across data subsets defined by social capital. Subset HH contains all loans for which both Borrower SocCap and Lender SocCap are above the 75th percentile of the population for all counties. Similarly, subset LL contains all loans for which both Borrower SocCap and Lender SocCap are below the 25th percentile of the population for all counties. The contents of subsets HL and LH are self-explanatory. There are three observations of interest in panel C. First, nearly one-half of the loans in our data (49.4%) were originated between borrowers and lenders in counties with high social capital (HH loans). Second, HH loans were 560 basis points less likely to default than LL loans. And third, loans with one counterparty (but not both) located in a high social capital county (HL and LH loans) were about 200 basis points less likely to default than LL loans.

Table 3, panel D shows that social capital is substantially higher on average in rural places than in urban places. Using the borrower market to make our comparisons (we find similar results using the lender market), both *Borrower SocCap* and *Lender SocCap* are statistically and economically larger in rural markets than in urban markets. Consistent with the data shown in the panel, the linear correlation between *Borrower SocCap* and a dummy equal to one for loans with rural borrowers equals 0.17, significant at the 1% level.

4. Estimation methodology

We test our hypotheses using a discrete-time logit model of loan default (Shumway 2001). The model is constructed as follows: Assume that each loan i ($i = 1,2,\ldots,N$) is originated during period $t=0$ and enters the model T times as a series of binary variables $D_i(1),\ldots D_i(T_i)$. $D_i(t)=1$ if loan i defaults during time period t and $D_i(t)=0$ otherwise, over the life of the loan. For example, measuring time in calendar quarters, the event history for a 3-year loan will be five zeros followed by a one (0,0,0,0,0,1) if the loan defaults in the sixth quarter after it was originated, but will be a string of twelve zeros (0,0,0,0,0,0,0,0,0,0,0,0) if the loan does not default.[9] The N separate event histories for each loan i are 'stacked' one on top of the other, resulting in a column of zeros and ones having $\sum_{i=1}^{N} T_i$ rows. We define D^*_{it} as a latent index value that represents the unobserved propensity of loan i to default during time period t, conditional on covariates X and W:

$$D^*_{it} = \mathbf{X_i}\boldsymbol{\beta} + \mathbf{W_{it}}\boldsymbol{\gamma} + \varepsilon_{it}$$

where $\mathbf{X}$ is a vector of time-invariant covariates, $\mathbf{W}$ is a vector of time-varying covariates, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are the corresponding vectors of parameters to be estimated, and ε is an error term assumed to be distributed as standard logistic. We further define:

$$D_{it} = 0 \text{ if } D^*_{it} \leq 0$$
$$D_{it} = 1 \text{ if } D^*_{it} > 0$$

Substituting the more compact notation $\mathbf{Z} = [\mathbf{X},\mathbf{W}]$ and $\boldsymbol{\phi} = \begin{bmatrix} \beta \\ \gamma \end{bmatrix}$, the probability that $D_{it} = 1$ is given by:

$$\text{prob}(D^*_{it} > 0) = \text{prob}(\mathbf{Z}\boldsymbol{\phi} + \varepsilon > 0)$$
$$\text{prob}(D^*_{it} > 0) = \text{prob}(\varepsilon > -\mathbf{Z}\boldsymbol{\phi})$$
$$\text{prob}(D_{it} = 1) = \Lambda(\mathbf{Z}\boldsymbol{\phi})$$

where $\Lambda(\cdot)$ is the logistic cumulative distribution function. The model is estimated using standard binomial logit techniques.

We specify the discrete-time logit model as follows to test the *ruralness*, *shared culture*, and *local lending* hypotheses:

$$\Pr[\, D_{it}=1 \,|\, \mathbf{Z}\,] = \Lambda[\, \textbf{\textit{borrower-lender}}_i,\ \textit{loan controls},\ \textit{lender controls},\ \textit{borrower controls},\ \textit{market controls},\ \textbf{\textit{year}}_t;\ \boldsymbol{\phi}\,] \quad (1)$$

where the binary dependent variable D_{it} equals one if loan i defaulted in quarter t, and equals zero in all other quarters during the life of the loan. The test variables are

[9] Loans that are prepaid prior to their contractual maturity, or right-censored loans (still performing but not yet mature at the end of our sample period), are also represented by strings of zeros.

contained in ***borrower-lender***, a vector of dummy variables comprised of either the four-way (RR, UU, RU and UR) or the six-way (RRL, UUL, RRNL, UUNL, RU and UR) taxonomy described above.

We include four different categories of control variables (*loan controls*, *lender controls*, *borrower controls*, *market controls*) shown elsewhere to be statistically significant determinants of SBA loan performance (e.g., Glennon and Nigro 2005). The vector of ***year*** dummies is included to absorb annual variation in loan default rates due to changing economic conditions, regulatory regimes, and the gradual adoption of small business credit scoring techniques during our sample period. Large banks began credit scoring small business loan applications in the early 1990s. In contrast, community banks did not begin using this new technology until some years later, and tended to use credit scores to complement rather than replace soft information collection (Frame, et al. 2001). Finally, there is evidence to suggest that rural banks were especially slow to adopt this technology (Cowan and Cowan 2006).

Table 4 displays descriptive statistics and definitions for all the variables used in these tests. Unless otherwise indicated as time-varying (TV), the variables are observed at the time of loan origination (LO). Three of the control variables bear special mention because their inclusion helps in identifying our hypotheses tests. First, *Distance* is the mileage "as the crow flies" between the borrower's home market and the market in which the lending office is located, and we expect this variable to be positively related to the probability of loan default (i.e., assessing borrower creditworthiness and monitoring borrower financial condition is more difficult far away from the lending office).[10] Including the *Distance* variable reduces the chances of capturing pure distance effects in the cross-market RU, UR, RRNL and UUNL coefficients. Second, *HHI* is the deposit-share Herfindahl index for banks and thrifts in the borrower's local market (constructed using the FDIC Summary of Deposits database). Rural banking markets are much more concentrated on average than urban banking markets; in our data, *HHI* averages 0.272 in rural markets but only 0.175 in urban markets.[11] By including *HHI* we reduce the chances of capturing market power effects in the borrower-lender coefficients; including the interaction term *HHI*Urban* (where *Urban* is a dummy variable equal to one in urban borrower markets) allows the marginal impact of market power to vary in rural and urban markets. We have no *a priori* expectations regarding the direction of these effects. If lenders are able to use local market power to restrict output, then default rates should be lower because it is the marginal loan applicants that will be denied loans. But if, as theorized by Petersen and Rajan (1994, 1995), market power gives lenders incentives to increase soft information-based lending, then default rates will be lower only if the investment in soft information improves credit screening and monitoring by more than

[10] The exact locations used to calculate *Distance* are the geographic Zip Code centroids for the borrower and the lender. In the regressions, we specify this variable as ln(*Distance* + 1).

[11] The U.S. Department of Justice characterizes local markets with HHIs exceeding 0.180 as "highly concentrated."

the increased output reduces the creditworthiness of the marginal borrower.[12] Third, *%SBA* is the percentage of the loan principal that is guaranteed by the SBA. We include this variable to control for the severity of potential moral hazard incentives, in which banks originating and holding loans with higher guarantees may have fewer incentives to carefully screen and monitor loans. We expect the probability of loan default to be positively related to this variable.

We specify the discrete-time logit model as follows to test the *social capital* hypothesis:

$$\Pr[\, D_{it}=1\,|\,\mathbf{Z}\,] \;=\; \Lambda[\, \textit{social capital}_i,\ \boldsymbol{\textit{borrower-lender}_i},\ \textit{loan controls},\ \textit{lender controls},\ \textit{borrower controls},\ \textit{market controls},\ \boldsymbol{\textit{year}_t};\ \boldsymbol{\phi}\,] \qquad (2)$$

where the *social capital* test variable is defined as either *Lender SocCap*, *Borrower SocCap*, or *Average SocCap*. We estimate equation (2) using various specifications to disentangle social capital effects from ***borrower-lender*** effects. In some specifications we remove the ***borrower-lender*** vector to generate baseline estimates of the *social capital* effects. In others we interact elements of the ***borrower-lender*** vector with *social capital* to test whether these two effects exist independent of each other, or whether one tends to dominate the other.

5. Results

Table 5 displays the full results for equation (1) estimated for 719,975 loan-quarter observations using the four-way borrower-lender taxonomy. The cells contain raw logit coefficient estimates, and a different borrower-lender dummy is excluded from each of the four columns. The results offer support for both the ruralness hypothesis (RR loans are less likely to default than UU loans). There is no support for the shared culture hypothesis for either rural loans (RR loans are not less likely to default than RU and UR loans) or urban loans (UU loans are not less likely to default than RU and UR loans). We take a closer look at these findings in Table 6, where we re-test these hypotheses for various data subsamples. Before doing so, we provide a brief discussion of the results for the control variables.

All but a handful of the control variables carry statistically significant coefficients, and the coefficient signs are economically sensible. As mentioned above, three of the control variables are perhaps more important than the other control variables for identifying our main hypotheses. First, default rates are positively related to borrower-lender distance (coefficient on *lnDistance* = 0.1037), an indication that including this

[12] Petersen and Rajan (1994, 1995) argue that a bank will be more willing to invest in costly information collection as its market power increases, because the reduction in the number of rival banks reduces the chance that its borrowers will switch banks in the future.

variable helps isolate pure borrower-lender distance effects from our hypothesized local lending effect. Second, default rates decrease with market concentration in rural places (coefficient on *HHI* = -0.3414), an indication that this variable helps separate loan default reduction from market power-related restrictions in rural loan supply from the hypothesized loan default reductions associated with ruralness.[13] Consistent with this, state-level restrictions on competitive branch entry are also associated with reduced loan default (coefficient on *Branch Restrictions* = -0.1059). Third, default rates increase with the size of the SBA loan guarantee (coefficient on *SBA%* = 1.6524), an indication that this variable helps control for moral hazard incentives associated with making guaranteed loans.

Age (the number of quarters since the loan was originated) is specified as a fifth-order polynomial, which allows us to capture the shape of the loan default hazard function without imposing structure on the data.[14] *Northeast*, *Midwest*, *Central*, *Southwest*, and *West* are dummy variables indicating the geographic region of the borrower; the negative coefficients on these variables indicate that default rates were highest in the omitted *Southern* region. Δ*Income* and Δ*Employment* are time-varying measures of state economic conditions and carry the expected negative coefficients. Loans to *New Businesses* are more likely to default, while loans to firms in the *Service* sector and loans to firms organized as *Partnerships* were less likely to default. Loans made by banks with substantial experience with SBA loans—*Certified* and *Preferred* loan providers—were less likely to default.

5.1. The ruralness and shared culture hypotheses

Table 6 displays the default odds ratios from the four-way borrower-lender specification of equation (1), estimated for three different data samples. Panel A shows the default odds for the full sample of 719,975 loan-quarter observations. Panel B shows the default odds for a smaller subsample of 638,691 observations, in which we exclude cross-market (RU and UR) loans for which the borrower and lender are located less than 25 miles apart. While these borrower-lender pairs are by definition cross-market loans, the borrower and lender are likely operating in the same local economic and informational environment; removing these suburban-fringe loans from the data may allow better identification for some of our hypothesis tests. Panel C shows the default odds for a subsample of 334,063 observations that further excludes loans made by banks

[13] Loan default rates also decline with market concentration in urban places, as indicated by the negative sum of the coefficients on *HHI* and *HHI*Urban* = -0.3414 – 0.2940 = -0.6354). In both cases, however, the statistical significance is weak.

[14] Our main results hold strongly when we replace this highly structured polynomial specification with a simpler vector of seven age-of-loan dummy variables.

with assets greater than $250 million (2012 dollars).[15] If the informational, institutional and cultural conditions found in rural markets result in better small business loan performance, it seems reasonable that these efficiencies would be especially strong at small rural banks where organizational structures tend to be flatter and less formal, allowing bankers and bank customers to interact more effectively and more frequently.

We find strong support for the *ruralness* hypothesis. In both panel A and panel B, loans between rural firms and rural banks (RR) are only about 89% as likely to default as loans between urban firms and urban banks (UU), all else held equal. This result becomes both statistically and economically stronger in panel C, where pure rural loans are only about 81% as likely to default as pure urban loans. Not only do small business loans between rural counterparties perform better than small business loans between urban counterparties, the lending efficiencies associated with ruralness are maximized at small rural lenders.

We find no evidence in support for *shared urban culture* in any of the three panels. Indeed, we find the opposite result in panel A, where pure urban loans are about 20% more likely to default than RU loans, and about 13% more likely to default than UR loans. This "anti-shared culture" result suggests that rural small business borrowers and rural lenders each bring something to the table—something that urban firms and lenders lack—that improves small business loan performance. However, this result weakens substantially in panel B which excludes suburban fringe loans, and disappears entirely in panel C which excludes larger community banks. We also find no support for *shared rural culture* in either panel A or panel B. But we find very strong support for shared rural culture in panel C, where pure rural loans are only about 72% as likely to default as RU loans, and only about 70% as likely to default as UR loans. These results suggest that shared borrower-lender culture is an important driver of our ruralness result, but these shared experiences and conditions are only effective for loans written by smaller rural community banks.

As discussed above, endogenous borrower decisions to search for loans outside of their local markets (RU and UR loans) may prevent us from drawing confident conclusions regarding the shared culture hypothesis. For example, when borrowers in *competitive* home markets (most likely urban markets, where average *HHI* is low) are denied credit and must search for a loan outside their home markets, one would expect a relatively high default frequency among these out-of-market loans, an outcome that is pooled with the shared culture hypothesis. But we find just the opposite result in panel A: D(UR) < D(UU). Similarly, when borrowers in *non-competitive* home markets (most likely rural markets, where average *HHI* is quite high) are denied credit and must search for a loan outside their home markets, one would expect a relatively low default

[15] Using this $250 million asset-size threshold, panel C retains approximately half (52%) of the SBA loans from panel B. In 1984, 85% of all U.S. commercial banks had assets less than this real dollar threshold; in 2012, 66% of all U.S. commercial banks had assets below this threshold.

frequency among these out-of-market loans, an outcome that is not pooled with the shared culture hypothesis. Again, we find just the opposite result in panel C: D(RU) > D(RR).

5.2. The local lending hypothesis

To test the *local lending* hypothesis, we re-specify equation (1) using the six-way borrower-lender taxonomy. The main results are displayed in Table 7. We find evidence in support of local lending efficiencies in urban markets. In panels B and C, urban firms borrowing locally (UUL) were, respectively, only about 89% and 80% as likely to default as cross-market urban borrowers (UUNL), after controlling for borrower-lender *Distance*. In contrast, rural firms borrowing locally (RRL) were no more or less likely to default than cross-market rural borrowers (RRNL), after controlling for borrower-lender *Distance*. Finding local lending effects for pure urban loans, but not finding them for pure rural loans, implies that the small business lending efficiencies associated with ruralness are not merely neighborhood effects but are at least to some extent portable across different rural markets.

5.3. The social capital hypothesis

Our initial tests of the *social capital* hypothesis are shown in Table 8. We use the full equation (2) specification, with the exception that the *borrower-lender* variables are removed. Each row displays partial results from a separate estimation. All three social capital variables have a statistically negative effect on loan default, with *Borrower SocCap* having the largest economic impact. For example, in panel A, a one standard deviation increase in *Borrower SocCap* reduces the odds of loan default by 10%, compared to a 6.4% decrease for *Lender SocCap*. These results are robust in the subsamples reported in panels B and C.

The final row in each panel of Table 8 shows the results from an alternative specification in which social capital is represented by the vector of borrower-lender market social capital quartiles from Table 3, panel C. In panel A, a loan is about 18% less likely to default if both the borrower and the lender are located in highest social capital quartiles (HH). Conversely, a loan is about 13% more likely to default if both the borrower and the lender are located in lowest social capital quartiles (LL). But only the HH result is robust across all three panels.

In Tables 9 and 10 we include both the *social capital* variables and the vector of *borrower-lender* location dummies in the specification. In addition, we interact the *social capital* variables with RR, to test whether *ruralness* effects dominate (or are dominated by) *social capital* effects, or whether these two effects exist independently in the data. Because interaction terms are difficult to interpret in logit models (Ai and Norton 2003), we estimate this specification using both a logit model (Table 9) and an OLS linear probability model (Table 10). The results are statistically similar, with the exception that the interaction term is statistically significant (and easy to interpret) in the OLS model. Thus, we limit our discussion to the results in Table 10.

As shown in column 1, the probability of loan default increases as lenders become more distant from borrowers (*lnDistance*), a result that is strongly robust to adding *borrower-lender* location and *social capital* variables to the regressions in the remaining columns. This result is consistent with both the prior empirical findings and the standard information-based conjecture that screening and monitoring small businesses is less effective for firms located further away from the lender. When the *borrower-lender* location dummies are included, the results are once again consistent with the *ruralness* hypothesis, especially in the small bank subsample. In column 2, panel A, pure rural loans are around 11% less likely to default than pure urban loans in the full sample, but this increases to 20% less likely in panel C.[16] These results are relatively robust to adding the *social capital* variables to the regressions. In column 3, a one standard deviation increase in *Borrower SocCap* is associated with an approximate 9% reduction in the chance of loan default.[17] The results for *Lender SocCap* and *Average SocCap* are similar, although it should be noted that the estimated impact of borrower social capital is always larger than the estimated impact of lender social capital.

In column 4 we add the social capital*RR interaction variables. The coefficient on this variable captures how a variation in social capital influences the default-reducing impact of ruralness, relative to purely urban (UU) loans. The test for the social capital hypothesis is ∂Default/∂Social, which is statistically negative. In column 4 of panel A, this derivative equals -0.00070 for RR loans; a one standard deviation increase in Borrower SocCap is associated with a 5.2% reduction in the chance of default, which is substantially smaller than the 11.1% social capital-induced reduction in the chance of default for non-RR loans. This suggests that ruralness effects and social capital effects are substitutes in loan default probability—that is, the default-reducing benefits of social capital have been partially absorbed into the institutions and practices of rural small business lending, which diminishes the marginal benefit of an additional unit of social capital in these markets. The test for the ruralness hypothesis is provided by ∂Default/∂RR, which is also statistically negative. In column 4 of panel A, this derivative equals -0.00077 for a loan with average borrower social capital; thus, a pure rural loan (RR) is 9.6% less likely to default than a pure urban loan (UU).

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[16] The first calculation is -0.0009/0.008 = -0.1125, where -0.0009 is the estimated coefficient on RR and 0.008 is the mean quarterly frequency of default in our data. The second calculation is -0.0016/0.008 = -0.2000.

[17] This calculation is -0.0012*0.594/0.008 = -0.0891, where -0.0012 is the estimated coefficient on Borrower Social and 0.594 is the standard deviation of Borrower Social in our data.

To double-check these estimated partial derivatives, we also performed a Gelbach decomposition to disentangle the marginal effects of RR and Borrower SocCap (Gelbach 2016). Using this approach, the full model is a linear specification (interaction variable removed) of the model in Table 10, panel A, column 4. Our results are robust. The Gelbach-decomposed marginal impact of RR is -0.000763 and the Gelbach-decomposed marginal impact of Borrower SocCap is -0.000687. Although both of these estimates are slightly smaller than the estimated partial derivatives in Table 10, their economic magnitudes are very similar.

6. Conclusions

Small Business Administration (SBA) 7(a) loan recipients are among the most credit-challenged entrepreneurs in our economy. Despite running businesses that are generating positive cash flows, these small business people are unable to obtain bank credit at reasonable market rates and terms without having a third-party guarantor. The SBA provides partial loan guarantees to entice banks to make credit available to these small firms, so credit risk is shared between banks and taxpayers. Nevertheless, the expected default rates on these loans are very high—historically, about one-in-six SBA loans defaults—so despite this risk-sharing arrangement, SBA lenders are placing no less capital at risk than other (non-SBA guaranteed) small business lenders.

In a market-based economy, it is important that grass roots, job-creating businesses have access to credit. But it is also important that any taxpayer funds used to subsidize credit extension to marginal small businesses be allocated efficiently. We find that SBA loans made by rural banks to rural borrowers are substantially less likely to default, all else equal, than SBA loans made by urban banks to urban borrowers. On average, purely rural loans are about 11% less likely to default than purely urban loans—and when the banks making these loans are small (assets less than $250 million), this "ruralness" advantage increases to about 19%. The direction of these results should not be surprising: Small banks tend to rely more than large banks on building customer relationships that reveal information about borrower creditworthiness, and rural communities tend to be information-rich places where "everyone knows each other's business." But the magnitudes of these results are substantial: Compared to SBA loans written by small rural banks, nearly one-quarter more SBA loans written by small urban banks end in default.

Are high levels of social capital—i.e., the sense of reciprocity and trustworthiness that arises from the existence of social networks (Putnam 2000)—in rural markets driving these results? Empirical measures of social capital are indeed higher in rural places than in urban places. Thus, it is plausible that a higher frequency of social interaction in rural areas reduces loan defaults because (a) borrowers work harder to avoid default because the costs of shame are high, and/or (b) lenders are better able to screen and monitor loans because the cost of information is low. We find that the probability of SBA loan default declines by about 5% with a one standard deviation increase in local social capital, but we find little evidence that this effect is stronger in rural markets.

We offer two non-mutually exclusive interpretations of these results. One possibility is that social capital (measured here and elsewhere as the availability of institutional networks within which people can interact and build trust) and ruralness (a way of life defined by a set of non-urban experiences, habits, and expectations) are largely independent phenomena and should be considered separate forces with regard to relationship lending. A second possibility is that our ruralness result reflects the existence of intra-family networks that lie outside the social infrastructures measured by social capital indices: That is, in rural places (where households are disproportionately comprised of related families with long social histories in the community) loan defaults are suppressed by family-related financial, commercial, and civic support that is less available in urban places (where households are disproportionately comprised of displaced nuclear families).

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Table 1

This table shows the distribution across years for a sample of 33,945 small business loans with seven-year maturities made by small U.S. commercial banks (assets less than $1 billion in 2000 dollars) under the Small Business Administration 7(a) loan guarantee program.

Year loan originated	Number of loans	Percent of sample
1984	544	1.60
1985	408	1.20
1986	597	1.76
1987	600	1.77
1988	555	1.63
1989	600	1.77
1990	675	1.99
1991	695	2.05
1992	848	2.50
1993	1,039	3.06
1994	1,577	4.65
1995	2,638	7.77
1996	1,593	4.69
1997	1,526	4.50
1998	1,438	4.24
1999	1,170	3.45
2000	1,114	3.28
2001	1,380	4.07
2002	1,453	4.28
2003	1,631	4.80
2004	1,754	5.17
2005	1,529	4.50
2006	1,298	3.82
2007	1,368	4.03
2008	1,334	3.93
2009	1,405	4.14
2010	1,579	4.65
2011	1,490	4.39
2012*	110	0.32
1984-2012	33,945	100.00

* Database ends in February 2012.

Table 2

This table compares the expected losses for SBA and non-SBA small business loans. Calculations for SBA loans are based on a random sample of 33,945 small business loans made under the Small Business Administration 7(a) loan guarantee program between 1984 and 2012. Calculations for non-SBA loans are based on estimates from Shibut and Singer (2014), additional FDIC data, and call report data.

	SBA loans	Non-SBA loans	
		Estimate A	Estimate B
Expected default rate (EDF)	0.176[1]	0.017[3]	--
Loss given default (LGD)	0.124[2]	0.570[4]	--
Expected loss (EDF*LGD)	0.022	0.010	0.008[5]

[1] The percentage of SBA loans in our data that defaulted.
[2] Calculation based on a 21.4% maximum loss of loan principal (100% minus the 78.6% SBA guarantee percentage in our data), a 10.3% loan interest rate for SBA loans (Glennon and Nigro, 2005, Table 2), a 7-year loan amortization schedule, a uniform distribution of loan default over time, and an 8% cost of capital.
[3] Average percentage of commercial and industrial (C&I) loans reported as past due 90 days or no longer accruing at U.S. commercial banks, 2000-2014 (call report data). Note: These data are unavailable prior to 2000.
[4] Average loss given default on small commercial and industrial (C&I) loans at banks resolved by the FDIC as reported in Shibut and Singer (2014).
[5] Average losses on commercial and industrial (C&I) loans at banks with assets between $300 million and $1 billion, 1992-2012. Data from peer group analysis performing on the FDIC website.

Table 3

This table displays loan default rates by borrower-lender locations and social capital for a sample of 33,945 small business loans with seven-year maturities made by small U.S. commercial banks (assets less than $1 billion in 2000 dollars) under the Small Business Administration 7(a) loan guarantee program between 1984 and 2001. ***, ** and * indicate differences from zero at the 1%, 5% and 10% levels, respectively.

Panel A: Four-way borrower-lender taxonomy

					Difference in means		
	borrower	**lender**	**# of loans**	**mean *Default***	**RU**	**UR**	**UU**
RR	rural	rural	7,056 (20.8%)	0.155	0.010	-0.013	-0.020***
RU	rural	urban	3,685 (10.9%)	0.145	--	-0.023**	-0.030***
UR	urban	rural	2,132 (6.3%)	0.168	--	--	-0.007
UU	urban	urban	21,072 (62.1%)	0.175	--	--	--

Panel B: Six-way borrower-lender taxonomy

			Difference in means				
	# of loans	**mean *Default***	**RRNL**	**RU**	**UR**	**UUL**	**UUNL**
RRL	5,282 (15.6%)	0.156	0.005	0.011	0.012	-0.011*	-0.039***
RRNL	1,774 (5.2%)	0.151	--	0.006	-0.017	-0.016*	-0.044***
RU	3,685 (10.9%)	0.145	--	--	-0.023**	-0.022***	-0.050***
UR	2,132 (6.3%)	0.168	--	--	--	0.001	-0.027***
UUL	15,239 (44.9%)	0.167	--	--	--	--	-0.028***
UUNL	5,833 (17.2%)	0.195	--	--	--	--	--

Panel C: High versus low social capital

					Difference in means		
	borrower	**lender**	**# of loans**	**mean *Default***	**HL**	**LH**	**LL**
HH	high	high	8,083 (49.4%)	0.133	-0.037***	-0.036***	-0.056***
HL	high	low	1,589 (9.7%)	0.169	--	0.001	-0.019*
LH	low	high	1,855 (11.3%)	0.169	--	--	-0.020*
LL	low	low	4,824 (29.5%)	0.188	--	--	--

Panel D: Borrower markets and social capital

	# of loans	**mean *Borrower SocCap***	**mean *Lender SocCap***
Borrower in rural place	10,741 (31.6%)	0.1677	0.1953
Borrower in urban place	23,204 (68.4%)	-0.0006	0.0103
Difference in means		0.1683***	0.1850***

Table 4

This table displays descriptive statistics for variables used to specify equations (1) and (2). The data are for 33,945 small business loans made between 1984 and 2012 under the SBA 7(a) loan program. TV indicates that the variable is time-varying. LO indicates that the variable is observed at loan origination.

			33,945 loans		719,975 loan-quarters	
		observed	**mean**	**std dev**	**mean**	**std dev**
Dependent variable						
Default	= 1 if loan defaulted in current period	TV	0.176	0.381	0.008	0.091
Borrower-Lender indicator variables						
RR	= 1 if Rural borrower, Rural lender	LO	0.208	0.406	0.255	0.436
RRL	= 1 if RR loan in local market	LO	0.156	0.363	0.201	0.401
RRNL	= 1 if RR loan across different markets	LO	0.052	0.223	0.054	0.225
UU	= 1 if Urban borrower, Urban lender	LO	0.621	0.485	0.607	0.488
UUL	= 1 if UU loan in local market	LO	0.449	0.449	0.481	0.500
UUNL	= 1 if UU loan across different markets	LO	0.172	0.377	0.127	0.333
RU	= 1 if Rural borrower, Urban lender	LO	0.109	0.311	0.085	0.279
UR	= 1 if Urban borrower, Rural lender	LO	0.063	0.243	0.053	0.224
Social capital variables						
Borrower SocCap	Social capital index in borrower market	LO	0.053	0.596	0.073	0.594
Lender Social	Social capital index in lender market	LO	0.069	0.583	0.093	0.586
Social Capital	Average of Borrower SocCap and Lender SocCap	LO	0.061	0.554	0.083	0.559
Loan controls						
Age	Age of loan in quarters	TV	20.258	13.966	15.656	12.751
Amount	Loan amount (in $1,000 of 2000 dollars)	LO	180.466	244.960	180.116	213.748
Distance	Miles between business and lending office	LO	62.284	208.246	48.890	178.417
lnDistance	Natural log of Distance	LO	2.584	1.536	2.422	1.466
Low Doc	= 1 if loan is a "low documentation" loan	LO	0.248	0.432	0.240	0.427
SBA%	Percent of loan principal guaranteed by SBA	LO	0.786	0.120	0.799	0.105
Lender controls						
Assets	Assets (in thousands of 2000 dollars)	LO	559,271	575,611	465,197	523,020
lnAssets	Natural log of Assets	LO	12.135	1.109	11.969	1.138
Certified	= 1 if SBA "certified loan provider"	LO	0.086	0.281	0.123	0.329

Preferred	= 1 if SBA "preferred loan provider"	LO	0.177	0.382	0.150	0.357

Table 4 (cont.)

			33,945 loans		719,975 loan-quarters	
		observed	mean	std dev	mean	std dev
Borrower controls						
Corporation	= 1 if organized as a corporation	LO	0.622	0.485	0.573	0.495
New Business	= 1 if new business start-up	LO	0.344	0.475	0.318	0.466
Partnership	= 1 if organized as a partnership	LO	0.062	0.242	0.075	0.264
Service	= 1 if in service sector (SIC code = I)	LO	0.343	0.475	0.338	0.473
Market controls						
⊿Income	Annualized % growth in state-specific personal income since loan origination	TV	0.232	0.217	0.183	0.193
⊿Employment	Annualized % growth in state-specific, SIC-specific employment since loan origination	TV	0.062	0.092	0.059	0.085
Branch Restrictions	= 1 if borrower in branching-restricted state	LO	0.417	0.493	0.517	0.500
HHI	Deposit Herfindahl index in borrower market	LO	0.198	0.118	0.204	0.123
Urban	= 1 if borrower in urban (MSA) area	LO	0.714	0.452	0.701	0.458
Northeast	= 1 if borrower in Northeast state	LO	0.107	0.309	0.116	0.320
Midwest	= 1 if borrower in Midwest state	LO	0.133	0.339	0.130	0.336
Central	= 1 if borrower in Central state	LO	0.217	0.412	0.216	0.411
Southwest	= 1 if borrower in Southwest state	LO	0.151	0.358	0.153	0.360
West	= 1 if borrower in Western state	LO	0.253	0.435	0.253	0.435

Table 5

This table displays the results from a discrete-time logit model of loan default model specified using the four-way borrower-lender taxonomy (RR, UU, RU, UR), estimated for 719,975 loan-quarter observations of SBA 7(a) loans originated by small commercial banks between 1984 and 2012. ***, ** and * indicate a statistically significant difference from zero at the 1%, 5% and 10% levels, respectively. Standard errors (not shown) are clustered at the lender level. All variables are defined in Table 4.

	[1]	[2]	[3]	[4]
RR	--	0.0714	0.0138	-0.1118**
RU	-0.0714	--	-0.0576	-0.1832***
UR	-0.0138	0.0576	--	-0.1255*
UU	0.1118**	0.1832***	0.1255*	--
Age	0.9165***	0.9165***	0.9165***	0.9165***
Age^2	-0.0864***	-0.0864***	-0.0864***	-0.0864***
Age^3	0.3525***	0.3525***	0.3525***	0.3525***
Age^4	-0.0065***	-0.0065***	-0.0065***	-0.0065***
Age^5	0.0000***	0.0000***	0.0000***	0.0000***
Amount	-0.1000	-0.1000	-0.1000	-0.1000
lnDistance	0.1037***	0.1037***	0.1037***	0.1037***
Low Doc	-0.9950	-0.9950	-0.9950	-0.9950
SBA%	1.6524***	1.6524***	1.6524***	1.6524***
*Low Doc*SBA%*	1.0886	1.0886	1.0886	1.0886
lnAssets	-0.0328	-0.0328	-0.0328	-0.0328
Certified	-0.1822***	-0.1822***	-0.1822***	-0.1822***
Preferred	-0.2426***	-0.2426***	-0.2426***	-0.2426***
Corporation	-0.0380	-0.0380	-0.0380	-0.0380
New Business	0.1605***	0.1605***	0.1605***	0.1605***
Partnership	-0.1950***	-0.1950***	-0.1950***	-0.1950***
Service	-0.3067***	-0.3067***	-0.3067***	-0.3067***
Δ*Income*	-1.7884***	-1.7884***	-1.7884***	-1.7884***
Δ*Employment*	-3.6347***	-3.6347***	-3.6347***	-3.6347***
Branch Restrictions	-0.1059**	-0.1059**	-0.1059**	-0.1059**
HHI	-0.3414**	-0.3414**	-0.3414**	-0.3414**
*HHI*Urban*	-0.2940	-0.2940	-0.2940	-0.2940
Northeast	-0.2050***	-0.2050***	-0.2050***	-0.2050***
Midwest	-0.2409***	-0.2409***	-0.2409***	-0.2409***
Central	-0.2797***	-0.2797***	-0.2797***	-0.2797***
Southwest	-0.0532	-0.0532	-0.0532	-0.0532
West	-0.1684***	-0.1684***	-0.1684***	-0.1684***
Intercept	-7.8198***	-7.8912***	-7.8336***	-7.7081***
year fixed effects	yes	yes	yes	yes
observations	719,975	719,975	719,975	719,975

Table 6

This table displays partial results from a discrete-time logit model of loan default model specified using the four-way borrower-lender taxonomy (RR, UU, RU, UR), estimated for three different samples of SBA 7(a) loans originated by small commercial banks between 1984 and 2012. ***, ** and * indicate a statistically significant difference from zero at the 1%, 5% and 10% levels, respectively, based on coefficient standard errors (clustered at lender level, not shown). Year dummies in all equations.

Panel A: Includes full sample of loans (N=719,975).

RHS variable omitted:	RR	RU	UR	UU
	[1]	[2]	[3]	[4]
RR	--	1.074	1.014	0.894**
RU	0.931	--	0.944	0.833***
UR	0.986	1.059	--	0.882**
UU	1.118**	1.201***	1.134**	--

Panel B: Excludes out-of-market loans (RU, UR, RRNL, UUNL) if Distance > 25 miles (N=638,691).

RHS variable omitted:	RR	RU	UR	UU
	[1]	[2]	[3]	[4]
RR	--	1.017	0.970	0.895**
RU	0.983	--	0.953	0.879*
UR	1.031	1.049	--	0.922
UU	1.118**	1.137*	1.084	--

Panel C: Excludes out-of-market loans if Distance > 25 miles **and** excludes banks if Assets > $250 million (N=334,063).

RHS variable omitted:	RR	RU	UR	UU
	[1]	[2]	[3]	[4]
RR	--	0.719***	0.698***	0.809***
RU	1.433***	--	0.971	1.160
UR	1.391***	1.030	--	1.126
UU	1.235***	0.888	0.862	--

Table 7

This table displays partial results from a discrete-time logit model of loan default model specified using the six-way borrower-lender taxonomy (RRL, RRNL, RU, RU, UUL, UUNL), estimated for three different samples of SBA 7(a) loans originated by small commercial banks between 1984 and 2012. ***, ** and * indicate a statistically significant difference from zero at the 1%, 5% and 10% levels, respectively, based on coefficient standard errors (clustered at lender level, not shown). Year dummies are included in all equations.

Panel A: Full sample (N=719,975).

RHS variable omitted:	RRL	RRNL	RU	UR	UUL	UUNL
	[1]	[2]	[3]	[4]	[5]	[6]
RRL	--	1.088	1.073	1.008	0.922	0.851**
RRNL	0.919	--	0.986	0.926	0.847**	0.782***
RU	0.932	1.014	--	0.939	0.859**	0.793***
UR	0.992	1.080	1.065	--	0.915	0.844***
UUL	1.085	1.181**	1.164**	1.093	--	0.923
UUNL	1.175**	1.279***	1.261***	1.184***	1.083	--

Panel B: Excludes out-of-market loans (RU, UR, RRNL, UUNL) if Distance > 25 miles (N=638,691).

RHS variable omitted:	RRL	RRNL	RU	UR	UUL	UUNL
	[1]	[2]	[3]	[4]	[5]	[6]
RRL	--	1.045	0.976	0.927	0.908*	0.808***
RRNL	0.957	--	0.934	0.887	0.869	0.774***
RU	1.025	1.071	--	0.950	0.931	0.828***
UR	1.079	1.127	1.053	--	0.98	0.872*
UUL	1.101*	1.150	1.074	1.021	--	0.890*
UUNL	1.237***	1.293***	1.207***	1.147*	1.124*	--

Panel C: Excludes out-of-market loans if Distance > 25 miles **and** excludes banks if Assets > $250 million (N=334,063).

RHS variable omitted:	RRL	RRNL	RU	UR	UUL	UUNL
	[1]	[2]	[3]	[4]	[5]	[6]
RRL	--	0.852	0.628***	0.653***	0.803***	0.641***
RRNL	1.174	--	0.737**	0.766*	0.942	0.752*
RU	1.593***	1.357**	--	1.040	1.279**	1.021
UR	1.532***	1.306*	0.962	--	1.231*	0.982
UUL	1.245***	1.061	0.782**	0.813*	--	0.798**
UUNL	1.561***	1.330*	0.980	1.019	1.254**	--

Table 8

This table displays partial results from a discrete-time logit model of loan default model estimated for 719,975 loan-quarter observations of SBA 7(a) loans originated by small commercial banks between 1984 and 2012. Each regression [1] through [4] is specified as in equation (2) using the four-way borrower-lender taxonomy (RR, UU, RU, UR). ***, ** and * indicate a statistically significant difference from zero at the 1%, 5% and 10% levels, respectively, based on coefficient standard errors (clustered at lender level, not shown). Year dummies in all equations.

Panel A: Full sample (N=719,975).				
Dependent variable	Independent variable	Estimated coefficient	Odds ratio	Odds ratio for 1 std dev increase in social capital
Default	*Borrower SocCap*	-0.1770***	0.838***	0.900
Default	*Lender SocCap*	-0.1132***	0.893**	0.936
Default	*Average SocCap*	-0.1751***	0.839***	0.902
Default	HH	-0.2007***	0.818***	--
	HL	-0.0423	0.959	--
	LH	-0.1392**	0.870*	--
	LL	0.1244**	1.132*	--
Panel B: Excludes out-of-market loans (RU, UR, RRNL, UUNL) if Distance > 25 miles (N=638,691).				
Dependent variable	Independent variable	Estimated coefficient	Odds ratio	Odds ratio for 1 std dev increase in social capital
Default	*Borrower SocCap*	-0.1744***	0.840***	0.902
Default	*Lender SocCap*	-0.1200***	0.887**	0.932
Default	*Average SocCap*	-0.1773***	0.838***	0.906
Default	HH	-0.2050***	0.815***	--
	HL	-0.0352	0.965	--
	LH	-0.1326*	0.876*	--
	LL	0.1419**	1.152*	--
Panel C: Excludes out-of-market loans if Distance > 25 miles **and** excludes banks if Assets > $250 million (N=334,063).				
Dependent variable	Independent variable	Estimated coefficient	Odds ratio	Odds ratio for 1 std dev increase in social capital
Default	*Borrower SocCap*	-0.1405***	0.869**	0.920
Default	*Lender SocCap*	-0.1011**	0.904*	0.943
Default	*Average SocCap*	-0.1390***	0.870**	0.925
Default	HH	-0.1823***	0.833**	--
	HL	-0.0225	1.023	--
	LH	-0.1373	0.872	--
	LL	0.0800	1.083	--

Table 9

This table displays partial results from a **discrete-time logit model** of loan default model estimated for 719,975 loan-quarter observations of SBA 7(a) loans originated by small commercial banks between 1984 and 2012. Each regression [1] through [8] is specified as in equation (2) using the four-way borrower-lender taxonomy (RR, UU, RU, UR). ***, ** and * indicate a statistically significant difference from zero at the 1%, 5% and 10% levels, respectively, based on coefficient standard errors (clustered at lender level, not shown). Year dummies in all equations.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Panel A: Full sample (N=719,975).								
lnDistance	0.0975***	0.1037***	0.1000***	0.0997***	0.1015***	0.1010***	0.1004***	0.0998***
RR		-0.1118**	-0.0887	-0.0952*	-0.0952*	-0.1022*	-0.0878	-0.0971*
RU		-0.1832***	-0.1699***	-0.1693***	-0.1687***	0.1675***	-0.1654***	-0.1639**
UR		-0.1255*	-0.1068	-0.1052	-0.1125	-0.1110	-0.1063	-0.1040
Borrower SocCap			-0.1770***	-0.1919***				
Borrower SocCap*RR				0.0518				
Lender SocCap					-0.1132	-0.1252**		
Lender SocCap*RR						0.0426		
Average SocCap							-0.1751***	-0.1956***
Average SocCap*RR								0.0663
Panel B: Excludes out-of-market loans (RU, UR, RRNL, UUNL) if Distance > 25 miles (N=638,691).								
lnDistance	0.0934***	0.0983***	0.0948***	0.0944***	0.0962***	0.0957***	0.0952***	0.0946***
RR		-0.1112*	-0.0895	-0.0965	-0.0935	-0.1008*	-0.0874	-0.0973
RU		-0.1285	-0.1174	-0.1171	-0.1134	0.1121	-0.1116	-0.1102
UR		-0.0808	-0.0612	-0.0596	-0.0638	-0.0620	-0.0583	-0.0555
Borrower SocCap			-0.1744***	-0.1919***				
Borrower SocCap*RR				0.0592				
Lender SocCap					-0.1200***	-0.1334**		
Lender SocCap*RR						0.0457		
Average SocCap							-0.1773***	-0.2013***
Average SocCap*RR								0.0743

Table 9 (cont.)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Panel C: Excludes out-of-market loans if Distance > 25 miles **and** excludes banks if Assets > $250 million (N=334,063).								
lnDistance	0.0720***	0.0524***	0.0489***	0.0483***	0.0520***	0.0519**	0.0505**	0.0502**
RR		-0.2114***	-0.1905***	-0.1963***	-0.1962***	-0.2015***	-0.1908***	-0.1981***
RU		-0.1483	-0.1507	-0.1510	0.1529	0.1541	0.1528	0.1541
UR		-0.1186	-0.1462	-0.1507	0.1315	0.1338	0.1411	0.1459
Borrower SocCap			-0.1405***	-0.1646***				
Borrower SocCap*RR				0.0555				
Lender SocCap					-0.1011**	-0.1167**		
Lender SocCap*RR						0.0367		
Average SocCap							-0.1390***	-0.1671***
Average SocCap*RR								0.0615

Table 10

This table displays partial results from an **OLS linear probability model** of loan default model estimated for 719,975 loan-quarter observations of SBA 7(a) loans originated by small commercial banks between 1984 and 2012. Each regression [1] through [8] is specified as in equation (2) using the four-way borrower-lender taxonomy (RR, UU, RU, UR). ***, ** and * indicate a statistically significant difference from zero at the 1%, 5% and 10% levels, respectively, based on coefficient standard errors (clustered at lender level, not shown). Year dummies in all equations.

Panel A: Full sample (N=719,975).								
lnDistance	0.0009*	0.0010**	0.0009*	0.0009*	0.0010*	0.0010*	0.0010*	0.0009*
RR		-	-0.0007*	-	-0.0007*	-	-0.0007*	-
RU		-	-	-	-	-	-	-
UR		-0.0013	-0.0012	-0.0011	-0.0012	-0.0012	-0.0012	-0.0011
Borrower SocCap			-	-				
Borrower				0.0008*				
Lender SocCap					-	-		
Lender						0.0007		
Average SocCap							-	-
Average								0.0009*
∂Default/∂RR				-		-		-
∂Default/∂Social				-		-0.00040		-
Panel B: Excludes out-of-market loans (RU, UR, RRNL, UUNL) if Distance > 25 miles (N=638,691).								
lnDistance	0.0009*	0.0009**	0.0009*	0.0009*	0.0009*	0.0009*	0.0009*	0.0009*
RR		-	-0.0007	-0.0008*	-0.0007	-0.0008*	-0.0007	-0.0008*
RU		-0.0012	-0.0011	-0.0011	-0.0011	-0.0011	-0.0011	-0.0011
UR		-0.0009	-0.0007	-0.0007	-0.0007	-0.0007	-0.0007	-0.0006
Borrower SocCap			-	-				
Borrower				0.0009*				
Lender SocCap					-	-		
Lender						0.0007		
Average SocCap							-	-
Average								0.0010*
∂Default/∂RR				-		-		-
∂Default/∂Social				-		-0.00041		-

Panel C: Excludes out-of-market loans if Distance > 25 miles **and** excludes banks if Assets > $250 million (N=334,063).

lnDistance	0.0006*	0.0004**	0.0004*	0.0004**	0.0004*	0.0004**	0.0004*	0.0004**
RR		-	-	-	-	-	-	-
RU		0.0021	0.0021	0.0021	0.0021	0.0021	0.0021	0.0021
UR		0.0011	0.0013	0.0013	0.0012	0.0012	0.0012	0.0013
Borrower SocCap			-	-				
Borrower				0.0008*				
Lender SocCap					-	-		
Lender						0.0005		
Average SocCap							-	-
Average								0.0006
∂Default/∂RR				-		-		-
∂Default/∂Social				-0.00052		-0.00038		-0.00051