Going the Extra Mile: Distant Lending and Credit Cycles*

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Abstract

We examine how competition amongst lenders exacerbates risk taking during a boom using a simple proxy for the risk of a bank's loan portfolio—the average physical distance of borrowers from banks' branches. The evolution of lending distances is cyclical, lengthening considerably during an economic upturn and shortening again during the ensuing downturn. More distant small business loans are indeed riskier for the bank, and greater lending distance is reflective of more generalized bank risk taking. As competition in banks' local lending markets increases, their local lending becomes riskier, and their propensity to make (risky) loans at greater distance increases.

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Descriptions of financial frenzies suggest lenders abandon caution in the midst of a boom and become more aggressive (or careless) in their lending (see, e.g., Aliber and Kindleberger, 2015; Minsky, 2008). A number of studies (e.g., Madalloni and Peydro, 2010; Mian and Sufi, 2009; Gianetti and Laeven, 2012; Lisowski, Minnis, and Sutherland, 2017) demonstrate the cyclicality of credit standards. However, not all lenders behave in the same way over the cycle. In particular, the importance of competition between lenders as a factor modifying behavior is relatively unexplored. In this paper, we examine this issue using an accessible proxy for risk taking—the extent to which lenders are willing to expand their loan portfolio by lending to borrowers at a greater physical distance from their branches.

A large theoretical and empirical literature argues that banks add value through their special ability to screen and monitor loans based on the private information they collect about current and prospective clients (e.g., Diamond, 1984; James, 1987; Diamond, 1991). This ability to produce information about hard to evaluate credits has historically been based on close interactions between bankers and potential borrowers (e.g. Liberti and Petersen, 2017, Petersen and Rajan 1994). As Stein (2002) suggests, "soft" information such as the firmness of a borrower's handshake, the cleanliness of her premises, or her punctuality in meetings might all reveal valuable information about the likelihood of repayment. Petersen and Rajan (2002) showed, however, that the adoption of information and credit scoring technologies in the 80s and 90s brought fundamental changes to the business models of banks. Slowly, but steadily, information technologies allowed lenders to substitute somewhat for local interactions in lending to small businesses. The average distance between banks and their borrowers increased steadily as these technologies improved.

Yet, at any point in time, available information and communication technologies determine the limits of the area within which a bank can lend safely. If a bank stretches to lend beyond this, it will screen and monitor the borrower less effectively, thus taking on more credit risk. Therefore, a faster-than-trend expansion of the average distance a bank lends at is either evidence of a rapid improvement of technology or suggestive of increased bank risk taking. If it reflects risk taking and not simply more rapid innovation, we should see that the more distant loans are associated with higher default rates, especially those made during the boom. A rapid drop in average distance in the bust should also follow such risk taking as banks become more conservative in lending.

The key contribution of the paper is to use the distance proxy for risk taking to examine the circumstances in which such risk taking is exacerbated. When many banks are competing for business in an area, they may have the capacity to make yet more loans after all the obviously safe loans are made (see, for example, Zentefis (2019)). It may be difficult for a branch manager to sit on un-lent cash if competitors seem to have no difficulty booking fees by making loans. Herd behavior or other forms of agency problems may therefore lead all banks in such areas to make riskier loans (see Rajan, 1994; Agarwal and Ben-David, 2014). Since such competition-induced agency problems increase bankers' effective risk tolerance, it should also increase their willingness to make loans at greater distances. Of course, in the bust, the pressure to make risky loans falls as all banks have difficulties. Banks can then go back to lending primarily to local borrowers. As a result, average distance should fall sharply. Areas with more competition between banks should therefore see more cyclicality in lending distances.

We test these ideas in this paper, exploiting two datasets that, when combined, offer information on the locations of borrowers and respective lenders of most small business loans originated in the U.S. over the last two decades. Specifically, we use the Community Reinvestment Act (CRA) data that stratifies the annual volume of loans originated by banks with total assets above $1 billion by the county of the loan recipient. We combine the CRA dataset with the Summary of Deposits (SOD) dataset that provides information on the branch network of all commercial banks operating in the United States to compute measures of the physical distance between the county of the loan recipient and the closest branch of its bank lender.[1]

We find that the long-run trend toward greater average distances between banks and their borrowers, initially documented by Petersen and Rajan (2002), persists in the past 20 years. Importantly, however, we find a significant cyclical component in the evolution of lending distances. Distances widen considerably in boom periods and then shorten again during the ensuing downturns. Between 2004 and 2007, banks increased their average distances from 175 miles to 350 miles. These distances, however, quickly slipped back to approximately 200 miles following the 2008 financial crisis.

This cyclical pattern in lending distances is observed after the inclusion of (borrower) county-year fixed effects and bank fixed effects. As the former accounts for loan demand in the county at a point in time, the results imply that in booms distant banks increase their lending to borrowers in a county relative to nearby banks, and do so more than in down years. Put differently, the results cannot be explained by differences in loan demand growth across counties. Since we also correct for bank-specific effects, it cannot be explained by changes in the composition of lenders in the economy over the cycle. This cyclicality also holds when we examine other points of the distribution of distances, such as the median. We further confirm that

[1] Recent papers on lending distance use either cross-sectional surveys (e.g., Petersen and Rajan, 2002; Brevoort and Wolken, 2008) or proprietary datasets obtained from a single financial institution (e.g., Agarwal and Hauswald, 2010; Agarwal and Ben-David, 2014).

the effect can be seen in banks of different size classes. To address the worry that changes in the nature of borrowers or loans over the cycle may drive the results, we show the effect exists in a specific borrower industry such as agriculture, where loans are fairly standard.

The next step is to establish that distant lending in the boom is, on average, riskier and hence amounts to additional risk taking by the banks. Towards this end, we use the Small Business Administration (SBA) loan-level dataset of government-guaranteed loans, which contains information on ex-post defaults or charge-offs (as we unfortunately do not have default data for loans in the CRA dataset). We find that distant loans originated in the pre-crisis boom years are significantly more likely to be charged-off *relative* to other loans issued by banks closer to borrowers in the *same* county during the *same* years, and this sensitivity of charge-offs to distance is more pronounced for loans originated in the pre-crisis boom years. Specifically, a one-percent increase in lending distance in 2006 and 2007 is associated with an increase in the charge-off probability that is between two and three times larger than that of a similar increase in lending distances in 2003. Furthermore, we find little evidence that banks obtain compensation through higher interest rates for the additional risks of lending at a greater distance. Our results suggest that, if anything, the sensitivity of interest rates to distance declines in the pre-crisis boom period.

Furthermore, we establish in two ways that such risk taking in small business lending is part of a broader pattern of risk taking by specific banks. First, we know the overall loan losses for each bank and hence can determine the average non-performing loan ratio for each bank over the 2007-2009 period. We find that the higher the average non-performing loan ratio of the bank, the more cyclical is its pattern in lending distance, suggesting that heightened small business loan distances can proxy for more general bank risk taking. Second, we use a returns-based measure of risk to gauge whether greater cyclicality in lending distances are indicative of banks' systematic risk exposures. Following Acharya, Pedersen, Phillipon, and Richardson (2017) and Meiselman, Nagel, and Purnanamdam (2018), we capture a bank's exposure to aggregate tail shocks through its average return during the 5% worst days for the market. We find that, in the cross-section of banks, the coefficient of correlation between a bank's average lending distance and each of our business cycle indicators is associated with this return-based measure of systematic risk. These results are indicative that the boom-bust cycles in lending distances are associated with banks' tendencies to accept exposures to tail risks.

Having established a cyclical pattern of risk taking, with distance being a good proxy for such behavior, we now turn to the central question of the paper: what are the conditions under which such risk-taking behavior emerges. We predict that banks whose *branches* are primarily in competitive banking markets should see a more pronounced cyclical pattern in average lending distance. Since such banks are likely to look for borrowers in less competitive areas, we should find a similar cyclical pattern in average borrowing distance for *borrowers* located in less competitive areas. Finally, distant loans made from a competitive area to a less competitive area should also have a cyclical pattern. We find evidence consistent with all of these predictions, measuring competition as the Herfindahl index for bank loans made in the respective county at the beginning of our sample period.

One reason banks in competitive areas may venture out to lend at a distance is that local lending may get particularly risky in boom times. Indeed, we find that charge-offs become far more sensitive to local market competition in the pre-crisis boom period than in other periods.

A bank that has the ability to reallocate resources (and thus lending) within its branch network from areas exposed to significant competitive pressures to areas with less fierce competition will have less pressure to take distance risk during the boom. Consistent with this conjecture, we find that the boom-bust cycle in lending distances is less pronounced for banks that have very different degrees of competition within their own branch networks. More precisely stated, banks with an above-median coefficient of variance of local market concentration across counties in their branch network have less cyclicality in distance lending than banks with a below-median coefficient of variation.[2]

We undertake a number of robustness checks. A voluminous literature argues that high concentration in an industry or region need not imply low competition – it could just mean that a more efficient producer has grabbed more market share. We address this and other concerns about the endogeneity of local competition with two alternative measures of bank competition. One is the timing of adoption of interstate banking deregulation. Deregulation occurred at different times for different geographies (e.g., Kroszner and Strahan, 1996; Stiroh and Strahan, 2003). If deregulation in a state occurred earlier, there was more time for competition to arise. We therefore use the natural log of the years between 1996 and the year when the state's banking market for loan origination was deregulated as a measure of competition. We find that the longer the time lapse since the adoption of interstate banking deregulation in the home market, the more amplified is the boom-bust cycle in lending distance.

For the second measure, we use a large bank's entry into a local market (typically through a merger or acquisition). For a large bank, the conditions in a specific small local market (where a particular branch is located) are unlikely to affect the overarching M&A decision. However, the presence of a large bank, which is able to send significant resources into the local market, is

[2] We also find, intuitively, that, among the subset of banks with below-median dispersion in their bank networks, the boom-bust cycle is more pronounced for banks that are exposed to uniformly high competitive pressures rather than banks that experience uniformly low competitive pressures.

likely to increase the level of local banking competition. We find that banks exposed to counties in which a big bank entered have a more amplified boom-bust cycle in lending distance.

That local competition affects risk taking during a boom suggests that not all lenders are enveloped in the frenzy. The natural implication is that explanations of financial frenzies that rely on overoptimistic participants need to be complemented with more traditional models describing how competition reduces bank franchise value (e.g., Keeley, 1990), induces herd behavior, distorts lender incentives, and exacerbates lending moral hazard.

Given that a sharp departure from the trend in distance between banks and borrowers is indicative of increased overall risk taking, distance is something that bank supervisors could usefully track. However, we note that the cycle in distance lending, even if risky, may have a silver lining. To the extent that banks push new lending technologies to their limit, it may give them a better understanding of these technologies, and a greater ability to lend at a distance during normal times. In other words, excess distance lending may expand the normal lending potential of banks as well as accelerate the secular trend in lending distance. Until this issue is further explored, any supervisory intervention needs to be measured.

We are obviously not the first to examine distance lending. A number of papers have also shown the cyclicality of cross-border lending (see, e.g., Gianetti and Laeven, 2012; De Haas and Van Horen, 2013; Kleimeier, Sander, and Sylvia, 2013; and Cerutti, Hale, and Minoiu, 2014). In domestic markets, Presbitero, Udell, and Zazzaro (2014) and Degryse, Matthews, and Zhao (2018) show that banks cut back on distant loans during the crisis. Our contribution is to tie both the increasing lending distance pre-crisis and bank risk taking more closely, and to identify the bank-specific circumstances in which such risk taking increases. In particular, the nature of competition in a bank's lending markets seems to play an important part in whether they go the extra mile.

1. Data Description

We obtain small business lending data from the Community and Reinvestment Act (CRA) small business loans database provided by the Federal Financial Institutions Examination Council (FFIEC) pursuant to Regulations 12 parts 25, 228, 345, and 195 of the aforementioned Act. This dataset contains information on the total number and volume of small business loans originated by each reporting financial institution in each county of the United States during a calendar year. Between 1996 and 2004, all commercial and savings banks with total assets exceeding $250 million were required to report their originations of small business loans by county of the borrower. Since 2005, the FFIEC raised the mandatory reporting asset size threshold from $250 million to $1 billion. Following this increase in the asset size threshold, the number of banks reporting to the CRA small business lending dataset declined from approximately 2,000 to 1,000. For the data analysis, we use the entire sample of banks available at any time. The empirical results are quantitatively and qualitatively similar when we use a constant sample of banks with more than $1 billion in assets.

We use the Summary of Deposits (SOD) database provided by the FDIC to obtain information about the geographic characteristics of all branches of depository institutions operating in the United States between 1996 and 2016. This dataset contains information on the geographical coordinates, location, and deposits of each branch in the United States. We complement the SOD dataset by assigning latitudes and longitudes to each branch address whenever geographic coordinate data are missing. We use information on the address, zip code, and county of the branch to retrieve the missing branch latitudes and longitudes via the Google

Geocoding Application Programming Interface (API). We also obtain financial characteristics of the commercial and savings banks from the quarterly Reports of Condition and Income (Call Reports) that banks file with the FDIC. Financial information on savings banks prior to 2012 comes from Thrift Financial Reports information available from the SNL Financial dataset.

We know from the CRA dataset the quantity of small business loans l_{bct} that a specific bank *b* has made to a specific county *c* in year *t*. We combine the SOD dataset on bank branch locations with information on the latitudes and longitudes of the geographic centroids of all U.S. counties. For the CRA dataset,[3] we assume that the closest geodetic distance d_{bc}, i.e., the length of the shortest curve between the centroid of borrower county *c* and the closest branch of bank *b*, represents the average distance between the borrowers from the bank in county *c* and the bank itself. We believe that this is a sensible measure of distance based on existing survey evidence suggesting that 59% of all US small banks receive small business loan applications at any branch, while 30% accept small business loan application at branches with loan offices, and only 11% accept applications online (FDIC, 2017). Thus, the value-weighted average loan distance for the bank *b* in year *t* will be $\frac{\sum_{c=1,N} l_{bct} d_{bc}}{\sum_{c=1,N} l_{bct}}$, where N is the total number of counties it has made loans to. For the entire economy, distance is $\frac{\sum_{b}\sum_{c=1,N} l_{bct} d_{bc}}{\sum_{b}\sum_{c=1,N} l_{bct}}$.

We compute other measures of geographic distance such as the distance between the population-weighted centroid of each county (rather than the geographical centroid) and the

[3] As described shortly, we use a slightly different approach for the SBA dataset because of differences in data availability.

closest branch of the bank, the distance between each borrower county centroid and the headquarters of each bank, and an indicator variable that takes the value of one if a bank has no branch in the county where it originated the small business loans, essentially coding out-of- versus in-county lending. We show in the Online Appendix that the main results are not sensitive to these alternative measures of distance between lenders and borrowers.

Since the CRA dataset does not contain loan by loan default or interest data, we also use the Small Business Administration (SBA), which contains a list of all SBA-guaranteed loans under the 7(a) program from 2000 to 2016.[4] It also contains loan-level information about the identity, address, city, and zip code of the borrowers and lenders as well as loan characteristics such as total amount, the amount of SBA's loan guarantee, initial interest rate, approval date, industry of the borrower, and loan status (performing/default). The dataset also includes information on the charge-off date and on the amount charged-off by the SBA on its loan guarantee when the loan is charged-off by the bank. Following Brown and Earle (2017), we exclude cancelled loans from the analysis because the cancellation may be at the initiative of the borrower.

For the SBA dataset, using the University of Chicago Geographic Information Service (GIS), we geocode the geographic coordinates of approximately 1 million borrowers and their lenders.[5] We are unable to locate the geographic coordinates of approximately 0.6% of the SBA borrowers in the dataset and we discard those observations. We compute the distance between borrowers and lenders in the dataset as the geodetic distance between the reported addresses of borrowers and respective lenders in the SBA dataset. This might seem more precise than our earlier method for the CRA dataset, but there is an important caveat -- the lender address is usually the bank's

[4] The 7(a) program is SBA's primary and most popular general-purpose, government-guaranteed lending program.
[5] We are grateful to Todd Schuble at the Research Computing Center of the University of Chicago for assistance in geocoding the geographic coordinates of the SBA borrowers' addresses

headquarters and not necessarily the closest branch. We could follow our earlier strategy and determine the closest bank branch. Unfortunately, the loan-level SBA dataset does not include the regulatory identifiers of the lenders that originated the SBA loans, and there is the potential for error in using the reported bank name (since they can be partial or truncated).[6] Therefore, the SBA dataset is more precise about borrower location, while the CRA dataset arguably provides more precision on lender location. Nevertheless, the cyclical properties of the distance proxies in both data sets are similar, allaying concerns about comparability or measurement error.

2. Lending Distances, Bank Lending, and Business Cycles

In this section, we document the main empirical patterns in banks' lending distances and the business cycle using the CRA dataset. We examine the matched CRA and SOD datasets to unearth basic descriptive facts about the evolution of lending distances over the past twenty years. After providing these statistics, we use regressions to more formally evaluate the role of the business cycle in shaping the relation between lending distances and changes in bank lending.

2.1. Summary Statistics

We begin our analysis by presenting basic information about the market for small business loans over the 1996 to 2016 sample period. Panel A of Table 1 shows that small business lending increased substantially over this period: the total volume of small business loans originated by CRA-reporting banks approximately doubled in current dollar terms from $115 billion in 1996 to $227 billion in 2016. The growth in the aggregate amount of small business loans was, however,

[6] For a limited set of lenders, we hand-matched the information in the SBA to the SOD and computed the geographic distance between the address of the borrower and that of the closest branch of the respective lender. In the Online Appendix, we use this alternative measure and we show that the cyclicality in the evolution of lending distances in the SBA data is not sensitive to this alternative definition.

not always steady over this period. During the 2001-2007 period, small business lending increased substantially to a peak of $324 billion in 2007 and subsequently saw a sharp decline to half of that amount during the Great Recession.

Small business lending is still mostly a local activity. Figure 1 and Panel A of Table 1 show that approximately 80% of all small business loans originated in the United States over the sample period went to borrowers that are less than 50 miles away from the closest branch of their bank lender, whereas only 7.5% of all small business loans went to borrowers that are located more than 1,000 miles away from the closest branch of their lender. The share of small business loans that are allocated toward distant borrowers has nevertheless fluctuated substantially over time. The plots of Figure 1 show that, between 2001 and 2007, distant lending increased at a faster pace than nearby lending and that the share of distant loans in the small business lending market increased substantially. The ensuing contraction in the 2007-2010 period was, however, more pronounced for distant loans and the share of the small business lending market accounted for by distant lending returned to pre-2003 levels in the years that followed the Great Recession.

Panel A of Table 2 reports summary statistics of the main variables used in the empirical analysis. The unit of observation is the (borrower) county-bank-year combination. The sample includes a bank-county combination from the start of the sample until the moment in which the bank disappears from the sample if the bank originated at least one small business loan in the sample. The sample includes approximately 5 million observations but only 2 million observations see non-zero growth in lending across two consecutive years. This large amount of zeros occurs because it is not uncommon for a bank to lend nothing to borrowers in a specific county through two consecutive years.[7] The average growth in bank lending to a county is 13.5%. Consistent with the intuition that banks from more competitive areas seek lending opportunities in less competitive areas, we also see the destination (borrower) markets are more concentrated, on average, than the origin markets where the bank's closest branch is located.

In Figure 2, we present key statistics about the evolution of lending distances over time. In Figure 2, Panel A, we plot the average distance of all small business loans weighted by their respective dollar amount from 1996 onward. The figure shows that average distances between borrower and lender trended positively over the sample period. From 1996 to 2016, average distance increased from approximately 100 miles to 250 miles. But the evolution of average lending distance did not always follow trend. Between 1996 and 2003, average distances rose steadily except for a decline in 2001. From 2004 until 2008, average-lending distances increased sharply above trend from approximately 175 miles to 350 miles and the Great Recession saw a significant pullback in average distances to pre-2004 levels.

The cyclical pattern holds when we compute alternative measures of lending distance between lenders and borrowers. Figure 2, Panel B shows the evolution of an equal-weighted average distance, which is determined as the simple average of the above lending distance computed bank by bank. On average, banks expanded their lending distances over the sample period and such expansion was strongly procyclical. In particular, average bank lending distances increased sharply between 2003 and 2007 and subsequently contracted in the ensuing years. This finding suggests that the previous results are not simply driven by an increase in the sample representation of larger banks that specialize in distant lending. In Panel C of Figure 2,

[7] To check that the results are not sensitive to this characteristic of our dependent variable by using alternative dependent variables (Table IA.1) and by limiting the sample to (borrower) county-bank combinations where we see more than 100 loans originated over time (Table IA.6)

we compute the proportion of all small business loans made to borrowers that are located in counties where lenders do not have a local branch. Similar to the previous results, this fraction increased between 1996 and 2016 and exhibits a strong boom-bust pattern around the events of the 2007-2009 financial crisis.[8]

We also examine the evolution of distance across several points of its distribution. Figure 3 presents the median lending distance (Panel A), the lower decile of lending distance (Panel B), and the upper decile of lending distance (Panel C) over the sample period. Consistent with the notion that small business lending is very local, the median distance in the sample varies from approximately 4 miles in 1996 to a peak of 8 miles in 2007. The evolution of lending distance is, nevertheless, similar across the different points of the distribution: lending distances exhibit an upward trend over the sample period and strong procyclicality, with rapid above-the-trend growth in lending distances between 2003 and 2008 and a subsequent sharp decline between 2008 and 2010. These patterns suggest that a shift in the entire distribution of lending distances rather than a few outliers drive the observed changes in average lending distance over time.

2.2. Empirical Results

In this section, we formally evaluate how business cycles mediate the relation between lending distance and changes in bank lending. We estimate an ordinary-least-squares (OLS) model of the change in the volume of small business loans originated by each bank in each county as a function of the distance of the bank to the county and the interaction between this distance and a measure of the state of the cycle (business/financial). Specifically, we estimate the following specification:

[8] In the online appendix, we show that the shape of these figures is not sensitive to the effects of mergers and acquisitions or to using a population weighted county-centroid to compute distance between borrower and lender.

$$\Delta\%\boldsymbol{SBL}_{\boldsymbol{bct}} = \boldsymbol{\alpha}_{\boldsymbol{ct}} + \boldsymbol{\gamma}_{\boldsymbol{b}} + \boldsymbol{\beta}_{\boldsymbol{1}}\boldsymbol{Ln}(\boldsymbol{Dist})_{\boldsymbol{bct}} + \boldsymbol{\beta}_{\boldsymbol{2}}\boldsymbol{Ln}(\boldsymbol{Dist})_{\boldsymbol{bct}}\times\boldsymbol{Z}_{\boldsymbol{t}} + \boldsymbol{\theta}\boldsymbol{X}_{\boldsymbol{bt}} + \boldsymbol{\epsilon}_{\boldsymbol{bct}} \quad (\mathbf{1})$$

where b indexes a bank lending to borrowers located in county c during year t. The dependent variable, $\Delta\%SBL_{bct}$, is the logarithmic change in one plus the volume of small business loans originated by bank b in county c during year t. Our main variable of interest, $Ln(Dist)_{bct}\times Z_t$, is the interaction between lending distance and a cycle indicator, Z_t, defined variously as the detrended change in real gross domestic product (GDP), the log difference in the US annual unemployment rate, or the standardized net percentage of banks increasing spreads of loan rates to small firms. We control for time-varying bank-level characteristics such as size and the shares of residential loans and commercial real estate loans in X_{bt}. The main coefficient of interest, β_2, captures whether the relation between lending distance and changes in bank lending is more or less pronounced depending on the state of the cycle. It is essentially a semi-elasticity of lending growth with respect to geographic distance and the state of the economy.

We include (borrower) county-by-year fixed effects α_{ct} and bank fixed effects γ_b. It is important to understand what they do. For instance, some counties may be neglected by banks (i.e., have few local banks) and hence, may receive a larger share of their small business credit from distant lenders. We need to control for the possibility that demand for loans in these counties grows relatively more in expansions (and relatively less in recessions). Therefore, we include (borrower) county-by-year fixed effects that absorb any time-varying unobserved county characteristics as well as local demand shocks. The bank fixed effects ensure that the relevant coefficients are estimated off variation in lending distance within a bank and not in the composition of lenders in the economy. Otherwise, a potential concern is that banks specializing in distant lending may become a larger share of the sample during expansions and subsequently lose share during recessions. In sum then, the coefficient of interest, β_2, is positive if in business cycle upswings, loan growth within a county comes disproportionately from banks with faraway branches (who typically lend closer to their branches in more normal times). We cluster standard errors at the county-level.

Table 3 presents results that are largely consistent with the descriptive statistics of Figures 2 and 3. The main coefficient on distance, β_1, is negative and significant across all three specifications suggesting that when the economy is in a neutral state and credit conditions are normal, greater distance to borrowers is associated with lower lending growth. More importantly, as the interaction term reveals, when the economy is booming, the negative relation between lending distances and changes in bank lending is significantly attenuated and potentially becomes positive provided that economic conditions are sufficiently good. The results of column (1) suggest that when the detrended real GDP series is one standard deviation above the mean, an increase in lending distance is associated with approximately no decline in bank lending. Similarly, the results of columns (2) and (3) suggest that a one-standard deviation decrease in unemployment rates and credit spreads approximately halves the measured negative relation between lending distance and bank loan growth.

To better understand the role that cycles play in shaping the relation between lending distance and credit supply, we consider an alternative approach in which we allow the effects of lending distance to vary non-parametrically over time. In particular, we implement the following specification:

$$\Delta\%\boldsymbol{SBL_{bct}} = \boldsymbol{\alpha_{ct}} + \boldsymbol{\gamma_b} + \sum_{\boldsymbol{t}} \boldsymbol{\beta_t}\, \boldsymbol{Ln(Dist)_{bct}} \times \boldsymbol{Year_t} + \boldsymbol{\theta X_{bt}} + \boldsymbol{\epsilon_{bct}} \quad \textbf{(2)}$$

where $Year_t$ is a set of dummy variables that equal to one at time *t* and zero otherwise and all other variables are defined as above. This alternative specification allows us to examine the relation between lending distances and changes in bank lending over the sample period without imposing parametric assumptions about how the relation between lending distances and changes in bank lending evolves over the business cycle.

In Figure 4, we plot the series of estimated coefficients, $\{\beta_t\}$, and corresponding standard errors overlaid on a line representing the detrended GDP growth series. The figure further suggests that recession years coincide with lower coefficients between lending distances and changes in bank lending and boom periods coincide with greater coefficients and even positive associations between lending distances and changes in bank lending. The univariate correlation between the series of year-specific effects of lending distance with the detrended real GDP series is 0.56. We interpret the results of this plot as supplementary evidence that the relation between lending distances and credit supply is strongly procyclical.

Next, we perform a battery of robustness checks to confirm the cyclical relation between lending distances and changes in bank lending. First, we examine whether this cyclical pattern is common across banks of different sizes, rather than limited to a few very large banks. In Table 4, we stratify the sample based on whether banks have less than $10 billion in total assets, between $10 and $50 billion in total assets, and more than $50 billion in total assets. The results reported in this table support the idea that the cyclical relation between lending distances and changes in bank lending is common to all bank sizes. Furthermore, in the online appendix we report that our results are not sensitive to using alternative dependent variables (Figure IA.1 and Table IA.1), other measures of distance (Figure IA.3, Tables IA.2 and IA.3), other business cycle indicators defined at the state and local-level (Table IA.4), winsorization of the main dependent variables (Table IA.5), limiting our sample to bank-county combinations whose number of total loans over the sample period exceed a minimum threshold (Table IA.6), and to re-estimating the main specification of the paper excluding one state at a time (Figure IA.6).

Another possible concern is that the composition of borrowers or loans changes over the business cycle – for example, during economic expansions loans may flow to industries that allow for more distance in lending based on differences in collateral type and quality. To examine whether the cyclical variation in distance is likely driven by changes in the pool of borrowers over the cycle rather than by changes in the willingness of lenders to make distant loans, we exploit a separate CRA dataset that only covers small agricultural loans. Agriculture is a monitoring-intensive industry where lenders must at least deploy some resources to check if the farmer is putting the loan to good use. Figure 5 suggests that small farm loan data also exhibit cyclicality in lending distance. While the average lending distance in the agricultural sector is less than for the rest of the economy, consistent with it being more monitoring intensive, the plot shows within-sector, above-trend growth in lending distances during economic expansions and subsequent declines in lending distance following recessions. In Table 5, we further show that the cyclical relation between lending distances and changes in agricultural bank lending holds in an empirical specification similar to that of equation (1). These results suggest that cyclicality is not simply driven by varying industry or loan composition.

Overall, the results in this section strongly support the idea that lenders are more willing to extend credit to distant borrowers during economic expansions and subsequently pull back to safety in the ensuing bust.

3. Lending Distances and Risk Taking

A potential explanation for the pattern we documented in the previous section is that during lending booms, credit standards become lax and lenders are more willing to take risks by originating loans to distant borrowers whose information is relatively harder to collect, evaluate, and monitor. In what follows, we empirically analyze a straightforward implication of this conjecture: that distant loans originated during booms should be relatively more likely to default.

3.1. Lending Distances and Loan-Level Loan Losses: Evidence from the SBA Loans

Unfortunately, the CRA dataset does not contain data on the performance of SBA loans made by the banks. Therefore, we use the Small Business Administration (SBA) loan-level dataset of government guaranteed loans, which does have loan-level information on ex-post defaults (also termed charge-offs). This dataset provides a rich set of information on the identities and addresses of borrowers and lenders, loan amounts, interest rates, and maturities of all government guaranteed loans approved since 2000. We use the listed addresses of the lenders and the corresponding borrowers to compute the lending distance for each loan in the dataset and to empirically examine the interplay between the business cycle and geographic distance in shaping the ex-post default of SBA loans.

3.1.1. Cyclical Lending Distance Patterns in the SBA Dataset

Before jumping to an empirical evaluation of the association between lending distances and loan performance over the business cycle, we investigate whether the cyclical distance patterns in the SBA dataset follow those of the broader CRA dataset. This step is necessary to support the idea that the overarching forces that induce lenders to go the extra mile for regular small business loans also apply in the SBA government-guaranteed lending market.

In Figure 6, Panel A we plot the average lending distance between the borrower and lender addresses of each loan in the SBA 7(a) dataset weighted by respective loan amount. Similar to the analysis of Figure 2, the weighted average lending distance substantially increases between

2003 and 2007 and later declines to the levels seen in the early 2000s following the financial crisis. In Panel B of Figure 6, we plot the average bank-level lending distance. Similar to the cyclical patterns observed for small business loans reported in the CRA sample, we observe that average bank-level weighted lending distance increases until the 2007-2009 financial crisis, subsequently declines as the crisis unfolds and rebounds between 2010 and 2016.

Next, we evaluate the cyclicality of lending distances in a regression analysis that follows the specification of equation (1). To implement this analysis, we aggregate loan amounts at the borrower county-bank-year level and we compute a measure of loan volume at bank-county-year level that is similar to that used in Table 3. We also compute the average lending distance of the bank to the county as the average distance of the bank to its borrowers in each county during that year. Specifically, we estimate the following specification:

$$\Delta\%\boldsymbol{SBA}_{\boldsymbol{bct}} = \boldsymbol{\alpha}_{\boldsymbol{ct}} + \boldsymbol{\gamma}_{\boldsymbol{b}} + \boldsymbol{\beta}_{\mathbf{1}}\boldsymbol{Ln}(\boldsymbol{Dist})_{\boldsymbol{bct}} + \boldsymbol{\beta}_{\mathbf{2}}\boldsymbol{Ln}(\boldsymbol{Dist})_{\boldsymbol{bct}} \times \boldsymbol{Z}_{\boldsymbol{t}} + \boldsymbol{\epsilon}_{\boldsymbol{bct}} \quad (\mathbf{5})$$

where *b* denotes the bank participating in the small business administration program, *c* the county of the borrower and *t* the year in which the loan was originated. The dependent variable, $\Delta\%SBA_{bct}$, is the logarithmic change in the volume of loans originated by bank *b* to borrowers located in county *c* during year *t*. The independent variable of interest, $Ln(Dist)$, is the average distance between bank *b* and its borrowers located in county *c*.[9] The business cycle indicators, Z_t, are those defined in the analysis of Table 3.

We estimate specification (5) using OLS and report the results in Table 7. Similar to prior analyses, the main coefficient on the interaction between the business cycle indicators and lending distances suggests that during expansionary periods, the relation between lending

[9] Unlike the measure of distance used in the previous analyses, this measure of distance may vary over time within a county-bank pair because borrowers may be at different places within the same county over time.

distance and changes in bank lending becomes more positive and vice-versa. We also implement and estimate a non-parametric specification akin to that of equation (2) in which we compute the year-specific elasticities of the change in bank lending with respect to lending distance. We plot the estimated coefficients and respective standard errors of this analysis in Figure 7. Similar to the analysis of Figure 4, the positive elasticities of changes in SBA lending with respect to lending distance coincide with expansionary periods and negative elasticities coincide with recessionary periods.

Overall, these results show that the evolution of distance in the government-guaranteed small business loan market exhibits cyclical patterns that are similar to those of the broader small business loan market.

3.1.2. Cyclical Lending Distance and Loan Default in the SBA Dataset

Having established that SBA loans behave similarly to regular small business loans, we proceed to exploit loan-level SBA data, which allows us to examine the evolution of the relation between ex-post loan defaults (charge-offs) and lending distance. If distant loans carry additional risks in the form of less effective screening and monitoring, we should see that distance is associated with higher default rates, especially for vintages originated during the boom.[10]

To empirically evaluate this conjecture, we implement the following empirical specification:

$$\mathbf{Pr}\;(\boldsymbol{CO_{ibct}} = \mathbf{1}) = \boldsymbol{\alpha_{ct}} + \boldsymbol{\gamma_b} + \sum_{\boldsymbol{t}} \boldsymbol{\delta_t}\, \boldsymbol{Ln(Dist)_{ibt}} \times \boldsymbol{Year_t} + \boldsymbol{\theta X_i} + \boldsymbol{\epsilon_{ibct}} \quad \mathbf{(6)}$$

where i indexes SBA government-guaranteed loans originated by lender b to small business borrowers located in county c during year t. The main variables of interest, $Ln(Dist)_{ibt} \times Year_t$,

[10] We confirm that our results are not sensitive to using a sample of SBA loans whose maturity is less than or equal to five years and that were originated prior to 2013 in order to allow for enough time for all loans to be worked-out by the end of the sample period.

are interaction terms of the log-distance between the addresses of the lender and the borrower and a series of year dummies. We further include county-by-year and bank fixed effects as well as additional controls for loan-level characteristics in the vector X_i, such as loan interest rates, loan maturities, and a full set of borrower-industry fixed effects. As before, standard errors are clustered at the county-level.

The inclusion of county-by-year and bank fixed effects ensure that the results are not driven by changes in local economic conditions or unobservable bank characteristics that affect the overall likelihood of default of small business loans originated in a county. We are, therefore, comparing the average outcomes of loans originated by nearby lenders relative to the average outcomes of loans to borrowers located in the *same* county that receive loans from distant lenders.

We present the results of this analysis in Figure 8. The evolution of the main coefficients presents a very clear pattern: over the initial years of the sample period, lending distances are not significantly related to the likelihood of charge-off. However, beginning in 2003 the relation between distance and the likelihood of charge-off becomes positive and statistically significant. The magnitude of the main coefficients increases over time and peaks for loan vintages originated in 2006. At the peak, the results suggest that a one percent increase in our measure of distance between borrower and lender is associated with a 2% increase in the likelihood of charge-off. This magnitude is economically significant especially when we benchmark it against an unconditional probability of charge-off of approximately 15% reported in Panel B of Table 2. After 2006, the relation between lending distances and likelihood of charge-off becomes less pronounced and turns statistically insignificant after 2010.

An important caveat of this analysis is that the government guarantee for SBA loans could intensify incentives to throw caution to the wind relative to other small business loans that do not include a guarantee. Lenders in a SBA guaranteed loan only absorb a predetermined fraction of potential loan losses (typically 15-25 percent of all losses) but earn full interest and fees accruing from the loan. This feature raises concerns about whether the results generalize to the broader lending market. To assess this possibility, we partition the sample based on whether the loan was originated under the regular 7(a) program or under the SBA Express program. The SBA Express program ensures an expedited review of documentation by the SBA (usually less than 24 hours) in exchange for a lower government-guarantee, 50% rather than the usual 75% or 85% guarantee of a regular 7(a) loan. In the Online Appendix (Figure IA.4) we repeat the analysis of Figure 8 for the subsets of regular 7(a) and SBA Express loans. We find that the relation between distance and charge-off is not significantly different in the subset of SBA Express loans that feature a lower government guarantee, alleviating the concern about the role of guarantees in our result.

3.1.3. Cyclical Lending Distance and Interest Rates on SBA Loans

Next, we investigate whether lenders require additional compensation on distant loans originated in the run-up to the financial crisis. One drawback is that interest rates on SBA loans are highly regulated. The SBA sets a maximum rate of the Prime rate + 2.25% for loans with principal amount of more than $50,000 and maturity of less than 7 years and Prime +2.75% for loans with principal amount of more than $50,000 and maturity of 7 years or more. In spite of these rate ceilings, there is some variation in the interest rate of loans approved by the SBA even on the same day, suggesting that not all loans are set at the maximum allowed interest rate.

We assess if lenders require additional compensation for distant loans originated in the run-up to the financial crisis, using an empirical specification similar to that of equation (6), in which we use the initial interest rate on the SBA loan rather than the likelihood of charge-off as the main dependent variable. We report the results in Figure 9. We do not observe any clear cyclical pattern in the sensitivity of interest rates to distance – if anything, the sensitivity of interest rates to distance declines in the lead up to the crisis, relative to earlier years. It increases only after the crisis (after 2010). This pattern is consistent with greater risk taking before, and conservatism after. What is abundantly clear is that lenders do not obtain additional compensation for the incremental ex-post default risk that they incurred in distant loans.

Overall, the results in this section are consistent with the idea that during expansionary periods, banks lower credit standards and accept the risks of extending credit to distant small business borrowers, who are relatively harder to evaluate and monitor.

3.2. Lending Distances and Banks' Nonperforming Loan Ratios

Having established that the stretch for distance is, in fact, risky, and not compensated by higher interest rates, let us turn to whether this reflects a broader pattern of risk taking in the banks. After all, small business lending is only a small portion of lending for many banks. If the patterns we have documented are not part of a broader pattern of risk taking, our results are still interesting, but of more modest importance for regulation and supervision, or economy-wide policy making.

Our first approach is to see whether lenders that experienced overall worse outcomes during the 2007-2009 period (not just from small business loans) originated relatively more loans to distant borrowers in the run-up to the 2007-2009 financial crisis and subsequently pulled back to local markets in response to heavy loan losses. This pattern would suggest that the banks that lend to distant small business borrowers are more willing to carry risks that are difficult to evaluate and quantify and that later materialize into large loan losses. These losses created significant balance-sheet pressures that induced these lenders to de-lever and retreat to the safety of local markets (e.g., consistent with the pattern observed in the cross-border lending evidence in DeHaas and Van Horen, 2012 and Gianetti and Laeven, 2012).

We begin this analysis by stratifying banks based on the median of the distribution of nonperforming loan ratio computed over the 2007-2009 period and plotting average distances over the sample period for above- and below-median nonperforming loan ratio banks. The results, shown in the left graph of Figure 10, are striking: above-median NPL banks exhibit a very pronounced boom-bust cycle in the average bank-level lending distances. By contrast, the average bank-level lending distances of below-median banks remain relatively steady over most of the sample and increase slightly following the financial crisis. These results are consistent with the notion that banks that reached farther out experienced larger overall loan losses.

To formally examine this association, we expand the specification in equation (1) by including a triple interaction between the nonperforming loan (NPL) ratios, lending distance, and the business cycle indicators. Specifically, we estimate the following model:

$$\Delta\%\boldsymbol{SBL_{bct}} = \boldsymbol{\alpha_{ct}} + \boldsymbol{\gamma_b} + \boldsymbol{\beta_1 Ln(Dist)_{bct}} + \boldsymbol{\beta_2 Ln(Dist)_{bct}} \times \boldsymbol{Z_t} \times \boldsymbol{NPL_b} + \boldsymbol{INT} + \boldsymbol{\theta X_{bt}} + \boldsymbol{\epsilon_{bct}} \quad (\mathbf{3})$$

where NPL_b measures each bank's average nonperforming loan ratio between 2007 and 2009 and all other variables are defined similarly to equation (1). We include all two-way interaction terms (*INT*) between the nonperforming loan ratio, lending distance, and business cycle indicators as well as county-by-year and bank fixed-effects in the above specification. We cluster standard errors at the county-level.

We report the results in Table 7. We find that lending distances are more positively (negatively) associated with changes in bank lending during expansionary (recessionary) periods, respectively. More importantly, the triple interaction between the NPL ratios, lending distances, and business cycle indicators reveals that greater loan delinquency amplifies the effect of the business cycle on the relation between distance and changes in bank lending. For example, the results of column (1) of Table 7 suggest that a one-standard deviation increase in the NPL ratio is associated with an increase of the interaction between lending distance and the detrended GDP by approximately 7% (0.002/0.027). These magnitudes indicate that banks experiencing greater loan losses experience more pronounced boom-bust cycle in distance lending. We obtain qualitatively similar inferences with the other cycle variables (though with larger economic magnitudes) in the other columns of Table 7.

We also expand the specification of equation (2) and employ a nonparametric approach that traces the marginal effects of lending distance on changes in bank lending over time at different points of the distribution of the nonperforming loan ratio. Specifically, we include a triple-interaction between lending distance, year dummies, and the NPL ratio:

$$\Delta\%\boldsymbol{SBL_{bct}} = \boldsymbol{\alpha_{ct}} + \boldsymbol{\gamma_b} + \sum_{\boldsymbol{t}} \boldsymbol{\delta_t}\, \boldsymbol{Ln(Dist)_{bct}} \times \boldsymbol{Year_t} + \sum_{\boldsymbol{t}} \boldsymbol{\lambda_t}\, \boldsymbol{Ln(Dist)_{bct}} \times \boldsymbol{Year_t} \times \boldsymbol{NPL_b}$$

$$+ \boldsymbol{INT} + \boldsymbol{\theta X_{bt}} + \boldsymbol{\epsilon_{bct}} \quad (\mathbf{4})$$

where our independent variable of interest is the triple interaction between lending distance, year dummies, and the NPL ratio at the bank level. As in other specifications, we also include two-way interaction terms (*INT*) between these variables as well as county-by-year and bank fixed-effect. Standard errors are clustered at the county level.

To better visualize how NPL ratios mediate the association between lending distance and changes in bank lending over time, we plot the time-series of estimated marginal effects of distance at different levels of the NPL ratio using the estimates from specification (4). We compute these marginal effects as:

$$MFX_t = \hat{\delta}_t + \hat{\lambda}_t \times NPL$$

where $\hat{\delta}_t$ represents the estimated year-specific elasticities of changes in bank lending with respect to distance from estimating specification (4) using OLS, $\hat{\lambda}_t$ the year-specific elasticities of changes in bank lending with respect to distance interacted with NPL. We evaluate and plot these marginal effects for a representative bank with NPL ratios two standard deviations above, and one with NPL ratios two standard deviations below, the average NPL ratio.

The chart on the right in Figure 10 represents the marginal effects of lending distance on changes in bank lending from estimating specification (4). The difference between the green (above-average nonperforming loan ratio) and red (below-average nonperforming loan ratio) suggest that banks that experienced greater nonperforming loan ratios between 2007 and 2009 show greater elasticities of changes in bank lending with respect to lending distances in the run-up to the financial crisis. This pattern suggests that above-average NPL ratio banks were more willing to take risks and increase lending to distant borrowers. We also find that this pattern reverses between 2008 and 2010, a period in which above-average NPL banks show lower elasticities of changes in bank lending with respect to lending distances. These last findings are in line with Presbitero, Udell, and Zazzaro (2014), Degryse, Matthews, and Zhao (2018), and Bord, Ivashina, and Taliaferro (2017) who find that banks experiencing greater delinquency ratios were more likely to retreat to their local markets.

3.3. Lending Distance and Returns-Based Measures of Tail Risk

The nonperforming loan ratio of each bank between 2007 and 2009 likely captures both idiosyncratic and systematic risks that these banks carried in their lending portfolios.[11] From a regulatory perspective, however, the documented cyclicality in lending distances is even more important if it is representative of exposures to systemic risks that were building up in the financial system before the crisis.

To gauge this possibility, we use a measure based on stock returns to capture the exposure of a bank to aggregate tail shocks. We follow Acharya, Pedersen, Phillipon, and Richardson (2017) and Meiselman, Nagel, and Purnanandam (2018) and measure exposure to systematic risks as a bank's average return during the 5% worst days for the market and bank industry stocks during the financial crisis. Acharya et al. (2017) find that this measure is related to a financial institutions' propensity to be undercapitalized when a system as a whole is undercapitalized, a concept that they refer to as the systemic expected shortfall. We explore whether investors perceive banks that exhibit more pronounced cyclical fluctuations in their lending distances as holding, on average, more systematic risk. The goal is not to claim that cyclicality in lending distance is a driver of systematic risk, but rather that banks with greater exposures to aggregate tail risk also exhibit greater cyclicality in lending distance, which in turn indicates that cyclicality in lending distance is a manifestation of a greater propensity for bank risk-taking.

In Table 8, Panel A we report summary statistics of the main variables used in this analysis. We measure lending distance cyclicality as the coefficient of correlation over the entire sample period between the business cycle indicator and the average lending distance of each bank. These

[11] In addition, a number of recent studies (Behn, Haselman, and Vig (2014), Begley, Purnanandam, and Zheng (2016), Plosser and Santos (2018), Blattner, Farinha, and Rebelo (2018), and Granja and Leuz (2019)) suggest that banks strategically understate risk exposures and underreport loan losses in response to capital constraints and regulatory incentives. This evidence suggests that the nonperforming loan ratio measured during the crisis may not accurately reflect differences across banks in their underlying portfolio risks.

descriptive statistics suggest that, on average, lending distance correlates positively with detrended GDP growth and negatively with changes in unemployment and credit spreads at the bank level. Average stock market returns in bad bank (market) days is -3.3% (-3.9%). Importantly, there is significant variation in the stock market performance of banks during these days suggesting considerable cross-sectional heterogeneity in bank exposure to systemic risks.

We follow a specification similar to that of Meiselman, Nagel, and Purnanandam (2018) to examine whether lending distance procyclicality is positively correlated with the return-based measure of systematic risk in the cross-section of banks. We report the results of this analysis in Panel B of Table 8. The results are indicative that more pronounced boom-bust cycles in lending distances are associated with a bank's propensity to accept exposures to tail risks. For instance, the results of column (1) suggest that when the coefficient of correlation increases from zero to one, the average returns on bad bank days decrease approximately one percentage point, which is approximately one standard deviation of the distribution of the dependent variables. The results reported in the other columns of Table 8 further support this association between procyclicality in lending distances and systemic risks.

In sum then, the move towards greater distance is both risky and uncompensated, and it is reflective of more generalized risk taking by the bank. Let us now turn to the central question: Which banks are likely to engage in such behavior?

4. Lending Distances and the Role of Competition

Having established that the cyclical pattern in lending distance is a good proxy for risk taking, we turn to the conditions under which risk-taking behavior emerges. Banks whose branches are primarily in competitive banking markets may find lending opportunities scarce and profit margins small within their local areas.[12] Herd behavior or other forms of agency could then induce branch managers to step outside their comfort zones and seek distant borrowers in less competitive areas rather than sitting on un-lent cash. We now examine whether banks whose branches are primarily in competitive banking markets see a more pronounced cyclical pattern in lending distance and whether we find a reciprocal cyclical pattern in average borrowing distance for borrowers located in less competitive areas. We also evaluate whether banks that have the ability to reallocate resources (and thus lending) within their branch network from areas exposed to significant competitive pressures to areas that are less exposed to fierce competition will be less pressured to take distance risk during the boom.

5.1 The Role of Competition in Home and Destination Markets

We begin by asking whether local competitive pressures amplify the cyclical relation between lending distances and changes in bank lending. To test this conjecture, we exploit variation in the intensity of competition at the county-level in the small business lending market. We base our measure of competition on the level of market concentration computed as the Herfindahl-Hirschman Index (HHI) in each county at the beginning of our sample.[13]

A simple partition of the raw data in Panel A of Figure 11 suggests that the cyclical variation in the average lending distance at the bank level is more pronounced in banks exposed to greater competition. We first group banks based on the average HHI of their home markets, i.e. the HHI of counties where the closest branch to the county of their borrower is located. We plot the average lending distances at the bank level for banks below and above the median HHI in their

[12] See, for example, Degryse and Ongena (2005) on the role of proximate bank competition on interest rates banks can charge.

[13] We also compute a measure of competition based on the HHI in the deposit market. The results are qualitatively and quantitatively when we use this alternative measure of market concentration. See Drechsler, Savov, and Schnabl (2017) for the use of deposit HHI as a proxy for bank competition.

home market. The lending distances of banks with below-median concentration in their home markets (the red line on the left side chart in Figure 11 Panel A) are more cyclical than those of banks with above-median concentration in their home market (the green line in that chart). For example, banks facing stiffer competition in their local branch markets, i.e. those with below-median HHI in their home markets expanded bank-level average lending distances from 80 miles in 2003 to approximately 130 miles in 2006 and saw their lending distances subsequently contract to less than 100 miles by 2010. The group of banks with above-median HHI, i.e. facing lower competition in their home markets, saw no such cyclical pattern and their bank-level average lending distances hovered 40 miles throughout the entire sample period. These figures suggest that banks exposed to greater competition see a more pronounced boom-bust cycle in lending distances.

One potential problem with the analysis above is that above- and below-median HHI banks could be systematically different in ways that affect the relation between lending distance and changes in bank lending but are not necessarily related with the local competitive pressures. To formally examine whether exposure to greater competition amplifies the cyclical relation between distance and changes in bank lending, we implement a specification similar to that of equation (3) and include a triple interaction between the level of market concentration, lending distance, and the business cycle indicators. Specifically, we estimate the following model:

$$\Delta\%\boldsymbol{SBL_{bct}} = \boldsymbol{\alpha_{ct}} + \boldsymbol{\gamma_b} + \boldsymbol{\beta_1 Ln(Dist)_{bct}} + \boldsymbol{\beta_2 Ln(Dist)_{bct}} \times \boldsymbol{Z_t} \times \boldsymbol{HHI_{bc}} + \boldsymbol{INT} + \boldsymbol{\theta X_{bt}} + \boldsymbol{\epsilon_{bct}} \quad (\mathbf{7})$$

where HHI_{bc} measures the county-level HHI of the small business lending market at the beginning of the sample period. We compute HHI_{bc} in the home market, destination market, and as the difference in HHI between the destination and home market. We include all two-way interaction terms (*INT*) between the HHI terms, lending distance, and business cycle. We cluster standard errors at the county-level.

Table 9 reports the results. We find that local bank competition is associated with greater cyclicality between lending distance and changes in bank lending. The interaction term between lending distances and business cycle indicators suggest that distance is more positively associated with changes in bank lending in expansionary periods and vice-versa. But more importantly, the triple interaction between the HHI measures, lending distances, and business cycle indicators supports the notion that competitive pressures amplify the business cycle effects. For example, the results of column (3) of Table 9 suggest that a one-standard deviation increase in the difference between the HHI of the destination and home markets raises the marginal effect of the interaction between lending distance and the detrended GDP by approximately 25% (0.008/0.035). These magnitudes indicate that when the difference in HHI between destination and home markets is large, lending distances and changes in bank lending are even more positively associated in expansionary periods and more negatively associated in recessionary periods. We obtain similar inferences with slight differences in economic magnitudes in other columns of Table 9.

We further investigate the role of market concentration by using a non-parametric approach similar to that of specification (4). Specifically, we estimate the following model:

$$\boldsymbol{\Delta\%SBL_{bct} = \alpha_{ct} + \gamma_b + \sum_t \delta_t\, Ln(Dist)_{bct} \times Year_t + \sum_t \lambda_t\, Ln(Dist)_{bct} \times Year_t \times HHI_{bc} + INT + \theta X_{bt} + \epsilon_{bct}} \quad \mathbf{(8)}$$

where our independent variable of interest is the triple interaction between the lending distance, year dummies, and the level of market concentration at home and destination markets. As in other specifications, we also include main effects and interactions *(INT)* between these variables as well as county-by-year and bank fixed-effect. As in previous specifications standard errors are clustered at the county level.

Similar to the approach of Figure 6, we compute and plot the marginal effects of lending distance on changes in bank lending using estimates obtained from an OLS regression of specification (4) and setting the levels of market concentration at two standard deviations above- and below-average. The results presented in Panel B of Figure 11, reinforce the idea that the boom-bust cycle in the marginal effects of lending distance is more pronounced when local branch markets are more competitive and less concentrated and when destination markets are less competitive and more concentrated. For instance, the plot on the left indicates that the marginal effects of lending distances on bank lending are larger during 2006 and 2007 when the home market is exposed to greater competitive pressures.

All this suggests that banks in competitive markets stretch into distant lending because heightened inter-bank competition makes local lending riskier in the boom – in other words, risk increases for them across the distance spectrum. To get at this, using the SBA data we relate the sensitivity of charge-offs in the market where the borrower is located to concentration in the local lending market and plot the results in Figure 12. We find that in the years leading to the crisis, loans made in more competitive markets experienced relatively greater charge-offs (though not in normal times or after the onset of the crisis). This might explain why lenders try and migrate out of those markets into more distant markets – of course, as we have seen, they experience high charge-offs in that distant lending also. Overall, the results in this section suggest that when lenders face diminishing profitable opportunities in core markets, they tend to extend credit to distant borrowers.

Overall, our findings suggest that interbank competition is a catalyst of cyclical risk-taking by banks. When lenders face fierce competition in their local branch markets and economic conditions are expansionary, they are more likely to step outside their local areas and make distant loans. The flip side of such expansion is that when economic and credit conditions take a turn for the worse, these lenders become more conservative and focus on their core markets by disproportionately cutting lending to distant borrowers.

5.2 The Role of Internal Capital Markets

Next, we examine whether banks that have the ability to redeploy resources from branches facing significant competitive pressures to branches that are less exposed to fierce competition are less inclined to lend to distant borrowers.

A simple measure of dispersion of lending opportunities within a bank's branch network is the coefficient of variation of the HHI in the branch network of each bank. A large coefficient of variation of the level of market concentration within a branch network indicates significant dispersion of market concentration relative to the average level of market concentration of the bank. We use this dispersion (relative to the mean) as a proxy for a bank's ability to use their branch network to reallocate resources from areas with significant competitive pressures where lending opportunities are scarce and profit margins small to areas where they face lower competitive pressures.

We begin to examine this conjecture by partitioning banks based on the coefficient of variation of the HHI of their local branch markets at the beginning of the sample period. Figure 13 stratifies the evolution of average bank-level lending distances based on above- and below-median coefficient of variation of HHI. The plot suggests that the boom-bust cycle in lending distances only exists in the subset of banks whose HHI dispersion relative to the mean is low. In this group, average bank lending distances approximately double between 2003 and 2007 and subsequently decline between 2008 and 2012.[14]

To further examine the role of internal capital markets in shaping the cyclical relation between lending distance and changes in bank lending, we also implement a specification similar to equation (7) in which we use the triple interaction between lending distances, business cycle indicators, and the coefficient of variation of HHI as the main independent variable of interest.

We report these results in Table 10. We use the detrended change in real GDP, change in the logarithm of the unemployment rate, and interest rate spreads on small business loans as our business and credit cycle indicators in columns (1), (2), and (3), respectively. The main coefficients suggest that the effect of the business cycle on the relation between lending distance and changes in bank lending is more pronounced when the standard deviation of the HHI is small. This result indicates that the relation between lending distance and changes in bank lending is incrementally more positive in expansionary periods for banks with low dispersion in the level of market concentration in their branch network relative to its mean.[15]

5.3. Robustness: The Role of Competition at Home and Destination Markets

A significant literature argues that high concentration in an industry or region need not mean low competition – it could just mean that a more efficient producer has grabbed more market share. We try to address these concerns using two alternative and more exogenous indicators of

[14] In the Online Appendix, we further split the group with low HHI coefficient of variation between those banks with uniformly low HHI across its branches and those with uniformly high HHI across its branches. Confirming our expectations, we find that the boom-bust cycle in lending distances is more pronounced in the subset of banks with low coefficient of variation that are exposed to uniformly low market concentration.

[15] This result is related to Cetorelli and Goldberg (2012), Gilje, Loutskina, and Strahan (2016) and especially Cortés and Strahan (2017) who show that commercial banks actively redeploy resources within their areas of operation in response to external shocks but show a preference for their core markets in doing so. Our result is slightly different in that we show that some banks never need to venture outside their core.

bank competition. First, we follow a broad literature that exploits the timing of adoption of interstate banking deregulation as a shock to competition in the banking industry (e.g. Jayaratne and Strahan, 1996; Kroszner and Strahan, 1999; Stiroh and Strahan, 2003; Cetorelli and Strahan, 2006). The idea is that out-of-state banks had more time to enter, ramp up competition, and drive out inefficient banks in states where deregulation occurred earlier. Second, we explore a large bank's entry into a local market (typically through merger). For a large bank, the conditions in a specific small local market are unlikely to affect its merger decision. But at the county-level, the entry of a large bank with a different business model and deep pockets is likely to disrupt local bank competition.

We use the natural log of the years between 1996 and the year when the loan origination state's banking market was deregulated as an additional measure of competition. We report these results in Table 11. Overall, the shorter the time elapsed since the adoption of interstate banking deregulation in the *destination* market, the more amplified the cyclical pattern in lending distance. Similarly, the result of columns (2) and (4) suggest that the longer the time elapsed since the adoption of interstate banking deregulation in the *home* market, the more amplified the boom bust cycle in lending distance. Interestingly, in column (6) where the measure of the credit cycle is spreads, the relevant coefficient is significant, albeit with the opposite sign to that predicted. Because the credit cycle indicator (Spreads) in this specification loads strongly on 2008 and 2009, we suspect that this sign is related to the specific effect of one of these years.

We also create an indicator that takes the value of one if a county saw a 5 percentage points increase in the deposit market share held by a large banking organization, which we define as a bank holding company whose total assets exceed $50 billion. Such a large increase suggests that a large banking organization either acquired another bank with local operations or significantly grew their operations in that county suggesting a more aggressive competitive environment. This idea is in line with the work of Claessens, Demirgüc-Kunt and Huizinga (2001) showing that foreign presence in the banking industry of a developing country is associated with lower net interest margins and more aggressive competition.

We report these results in Table 12. The results of columns (2), (4), and (6) show that when a large banking organization substantially increases its presence in the home market of a bank, the cyclical pattern in lending distance is substantially amplified as local banks react to intensifying competitive pressures in their home markets from large banking organizations by going the extra mile and increasing their distant lending during expansionary periods. Similarly, the results in columns (1) and (3) suggest that distant lending increases less during expansionary periods in counties of borrowers where large banking organizations significantly increase their presence, consistent with the idea that lenders avoid going the extra mile to counties that are experiencing increasing competitive pressures. We do not, however, find a significant effect in column (5) when cyclicality is measured by spreads. Overall, though, the results in these columns support the idea that competitive pressures in local lending markets during expansionary periods induce banks to lend to borrowers that are farther away.

6 Discussion of Results and their Relation to the Literature

Our paper adds more evidence to support existing findings in a number of areas, so it is important to identify the specific contribution of the paper. First, since Petersen and Rajan (2002) a series of papers show that geographic distance still plays a major role in lending decisions. For instance, Agarwal and Hauswald (2010) show that physical distance improves the ability of lenders to produce soft information and extend credit to small businesses, Granja, Matvos, and Seru (2017) show that geographic proximity is a significant determinant of who acquires failed banks in the economy, and Nguyen (2019) finds that bank branch closures are associated with declines in small business lending. We find that the secular trend toward greater lending distances documented in Petersen and Rajan (2002) persists but we also uncover a significant cyclical component to such distances, which is not only new but also suggests that banks that go the extra mile indeed take undue risks. Proximity still seems to matter in controlling risks.

Second, a number of studies examine the cyclicality of risk taking in the economy. Rajan (1994), Ruckes (2004), Dell'Aricia and Marquez (2006), Zentefis (2018) and Kopytov (2019) study how cyclical lending standards can emerge in equilibrium in the economy.[16] A series of papers (e.g. Madalloni and Peydro (2010), Mian and Sufi (2009), Gianetti and Laeven (2012), Dell'Aricia, Igan, and Laeven (2012), De Haas and Van Horen (2013), Kleimeier, Sander, and Sylvia (2013), Cerutti, Hale, and Minoiu (2014), Jimenez, Ongena, Peydro, and Saurina (2014), Ioannidou, Ongena, and Peydro (2015), and Lisowsky, Minnis, and Sutherland (2017)) provide empirical evidence of the cyclicality of credit standards. In domestic markets, Degryse, Matthews, and Zhao (2018) and Presbitero, Udell, and Zazzaro (2014), suggest banks are quicker to drop their distant clients in a downturn.

We add to this literature by showing that a sharp departure from trend distance between banks and borrowers is indicative of increased risk taking and by documenting strong cyclicality of lending standards in the small business lending market.

Perhaps most importantly, though, we attempt to understand why such behavior emerges, and in which markets or banks. Hellmann, Murdock, and Stiglitz (2000) suggest that bank

[16] In an interesting recent paper, Kopytov (2019) describes why lending distance might increase as the cycle gets long in the tooth – essentially lending margins erode, therefore loans are riskier, and diversification (and hence distant loans) becomes more important for banks to avoid the expected costs of distress. Presumably margins erode more in competitive areas, hence there should be greater search for distance in those areas. Kopytov's model would suggest an increase in diversification in all areas, but particularly in competitive ones. Our evidence suggests an increase in distance primarily in competitive areas (see Figure 11, Panel A).

competition can undermine prudent bank behavior and induce banks to take excessive risks. On the other hand, Boyd and De Nicoló (2005) argue that concentration in banking markets could encourage higher interest rates, which, in turn, could heighten moral hazard concerns with bank borrowers. The former paper predicts more risk taking in competitive markets (as does Keeley, 1990) while the latter suggests potentially more losses in concentrated banking markets.[17] Rajan and Ramcharan (2015) suggest that the interplay of interbank competition and a positive shock to agriculture exacerbated the boom-bust cycle in land prices in the run-up to the Great Depression. Our findings go further to show that banks exposed to greater competitive pressures seem to go out on a limb to make distant loans that pose additional risks, but primarily in the expansionary phase of the cycle.

We also show that banks that are diversified across areas with differing degrees of competition do not succumb to such risk taking behavior. This may explain the finding in Morgan, Rime, and Strahan (2004) that greater banking integration spurred by interstate banking deregulation in the United States reduced business cycle volatility at the state-level. Our findings also suggest that a focus on inter-bank competition and the incentives thereof is essential to complement explanations of boom-bust episodes relying on over-optimism or other forms of irrationality. It would otherwise be hard to explain why specific types of banks as well as banks in certain areas seem more immune to the frenzy that overtakes bank lending episodically.

Apart from helping us understand bank behavior, we believe our study's finding that a sharp departure from trend distance between banks and small borrowers is indicative of increased risk

[17] In an interesting set of papers, Dreschler, Savov, and Schnabl (2017, 2019) show that greater bank competition at the local deposit level (different from our focus on competition in lending markets) facilitates the pass-through of monetary policy to interest rates – so they would suggest greater fluctuation in credit availability from banks raising money from concentrated deposit markets over the cycle as they expand deposit financing in periods of low interest rates and contract it as interest rates rise.

taking could be useful to bank supervisors. Since distance is easily measurable, it is a metric that bank supervisors could track as they monitor lending standards in the economy. Of course, we realize that doing so would still be subject to Goodhart's Law, i.e., as soon as supervisors start using it as a measure, banks will behave in ways that make it less useful. Moreover, as noted in the introduction, any supervisory intervention should also recognize the potential impact of any intervention on banks' incentives to innovate and learn as they stretch to lend at a distance.

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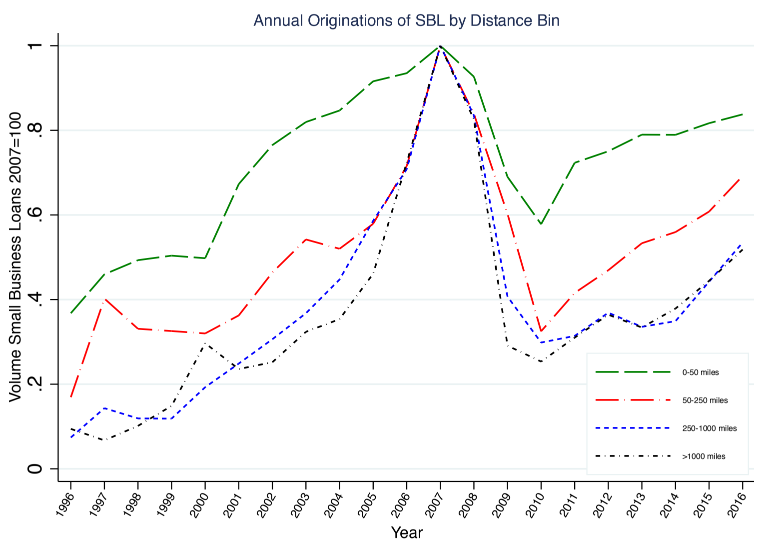
Figure 1: Time Series of Small Business Loan Originations by Distance Bin

Figure 1 shows the total amounts of small business loan origination and corresponding shares of the total small business loans originated in each of four bins representing the minimum distance between the borrower's county centroid location and the closest branch of the lender. The first bin represents distances between 0 and 50 miles, the second bin represents distances between 50 and 250 miles, the third bin represents distances between 250 and 1,000 miles, and the fourth bin represents borrowers and lenders that are more 1,000 miles apart. Data for this figure is computed using the CRA Small Business Lending and the SOD datasets.



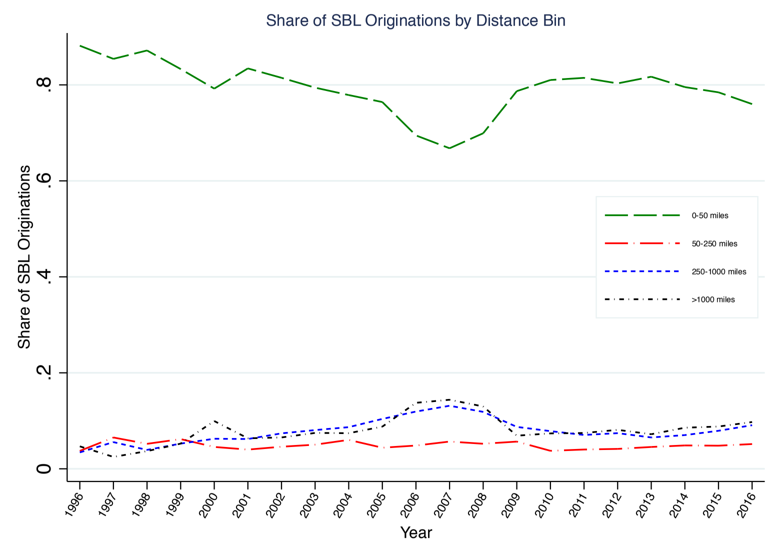
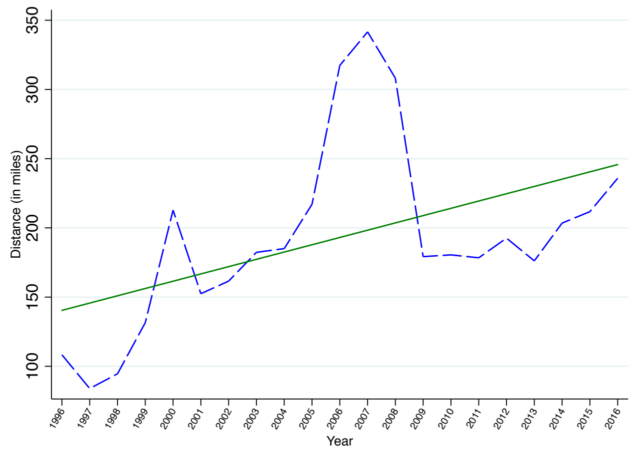


Figure 2: Evolution of Lending Distances

Figure 2 shows three plots. Panel A plots the average weighted distance of all small business loans over time. Lending Distance for each loan is computed as the geodetic distance between the borrowers' county centroid and the banks' closest branch. Panel B plots the bank equal-weighted lending distance over time. To compute the bank equal-weighted lending distance, we initially compute the average lending distance for each bank-year combination and then average across all banks in each year. Panel C plots the percentage of loans that are originated to borrowers that are located in counties where the lender does not have a branch. Data for all figures is obtained from the combination of the CRA and SOD datasets.

Panel A: Average Lending Distance (Volume-Weighted)



Panel B: Average Lending Distance (Equal-Weighted across Banks)

Panel C: Proportion of Lending to Counties outside Branch Network (Volume-Weighted)

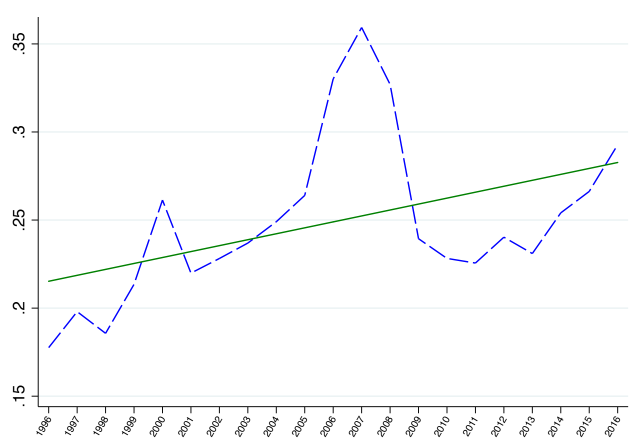
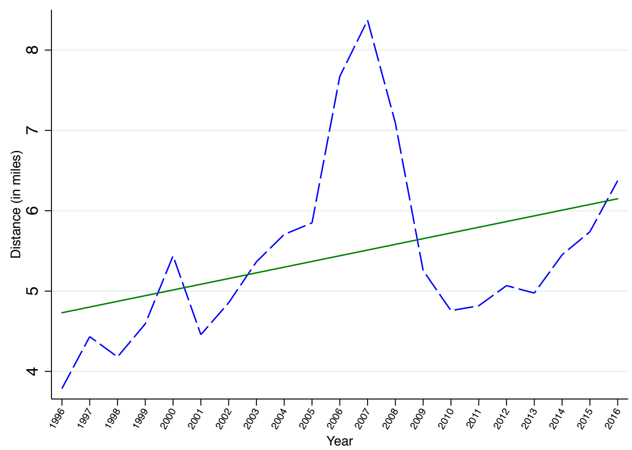


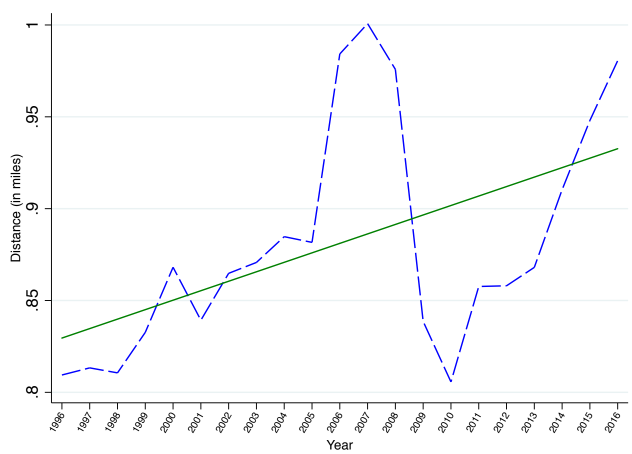
Figure 3: Evolution of Lending Distances: Other Points of the Distribution

Figure 3 shows three plots. Panel A plots the median of the weighted distance of all small business loans over time. Lending Distance for each loan is computed as the geodetic distance between the borrowers' county centroid and the banks' closest branch. Panel B plots the lower decile of the weighted distance of all small business loans over time. Lending Distance for each loan is computed as the geodetic distance between the borrowers' county centroid and the banks' closest branch. Panel C plots the upper decile of the weighted distance of all small business loans over time. Lending Distance for each loan is computed as the geodetic distance between the borrowers' county centroid and the banks' closest branch. Data for all figures is obtained from the combination of the CRA and SOD datasets.

Panel A: Median of Lending Distance (Volume-Weighted)



Panel B: Lower Decile of Lending Distance (Volume-Weighted)



Panel C: Upper Decile (Volume-Weighted)

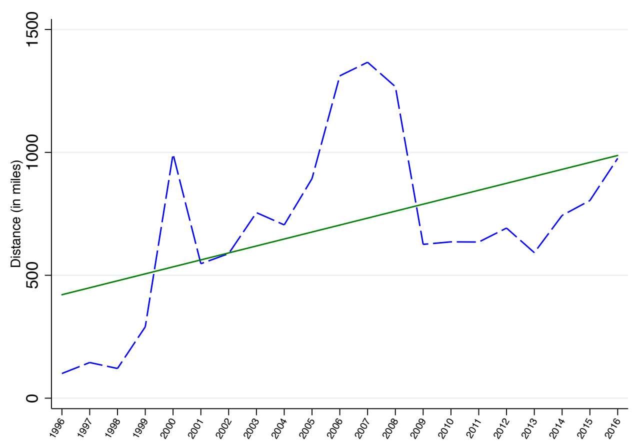


Figure 4: Distance and Lending Growth over the Business Cycle

Figure 4 plots the estimated coefficients from a regression of the log change in the volume of small business loans by a lender to borrowers located in a county on a series of interactions between lending distance and a set of dummy variable representing each year in the sample. Specifically, we plot the series of estimated coefficients β_t and associated 99% confidence intervals estimated from OLS regression of the following empirical specification: $\%\Delta SBL_{bct} = \theta_{ct} + \omega_b + \sum_t \beta_t Distance_{bct} \times Year_t + \Gamma X_{bt} + \epsilon_{bct}$. The shallow triangles connected by the dashed line represent the detrended GDP growth series (HP-filtered). Data for this figure is computed using the CRA Small Business Lending and the SOD datasets.

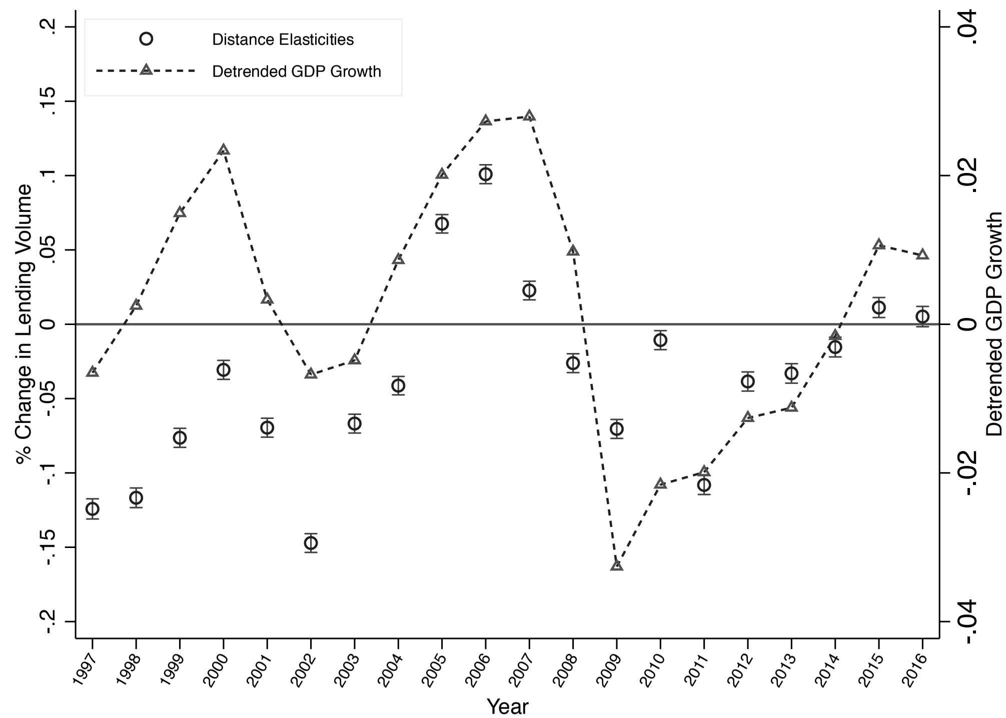


Figure 5: Evolution of Lending Distance: Small Farm Lending Dataset

Figure 5 plots the average weighted distance of all small farm loans over time. Lending Distance for each loan is computed as the geodetic distance between the farms' county centroid and the banks' closest branch.

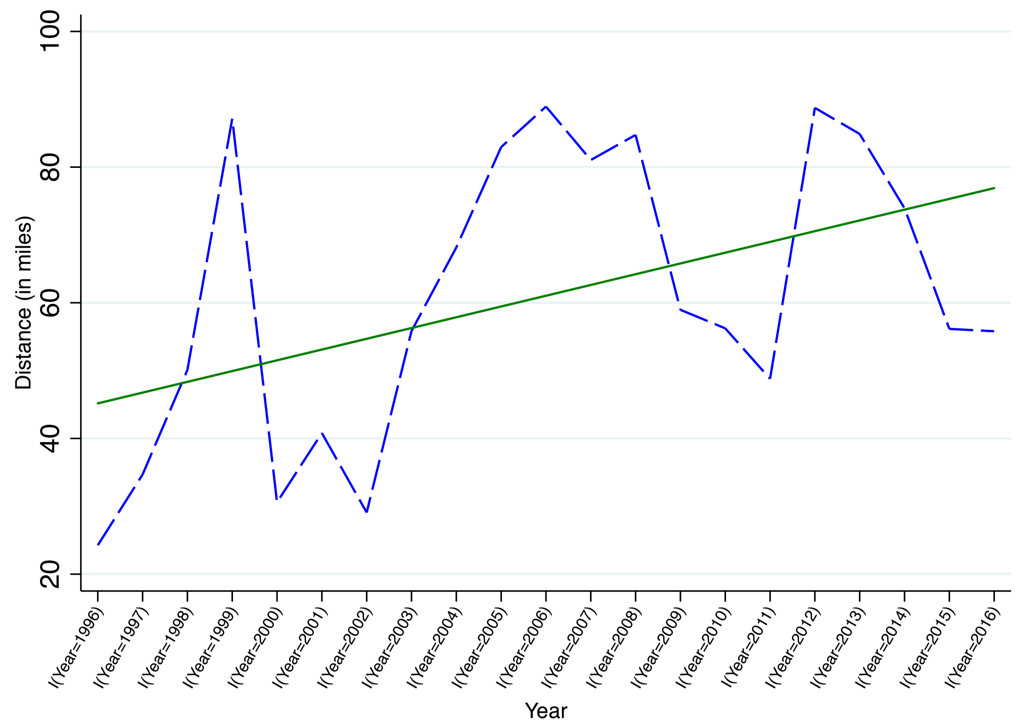
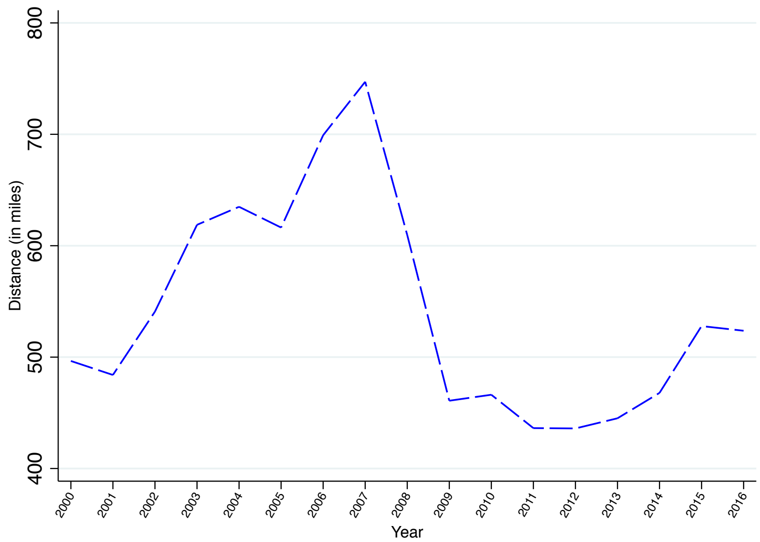


Figure 6: Evolution of Lending Distances in the Small Business Administration Dataset

Figure 6 shows two plots. Panel A plots the average distance of all small business administration loans over time. Lending Distance for each loan is computed as the geodetic distance between the lender and borrower addresses listed on the SBA dataset. Panel B plots the bank equal-weighted lending distance over time. To compute the bank equal-weighted lending distance, we initially compute the average lending distance for each bank-year combination and then average across all banks in each year. Data for all figures is obtained from the Small Business Administration

Panel A: Average Lending Distance (Volume-Weighted)



Panel B: Average Lending Distance (Equal-Weighted across Banks)

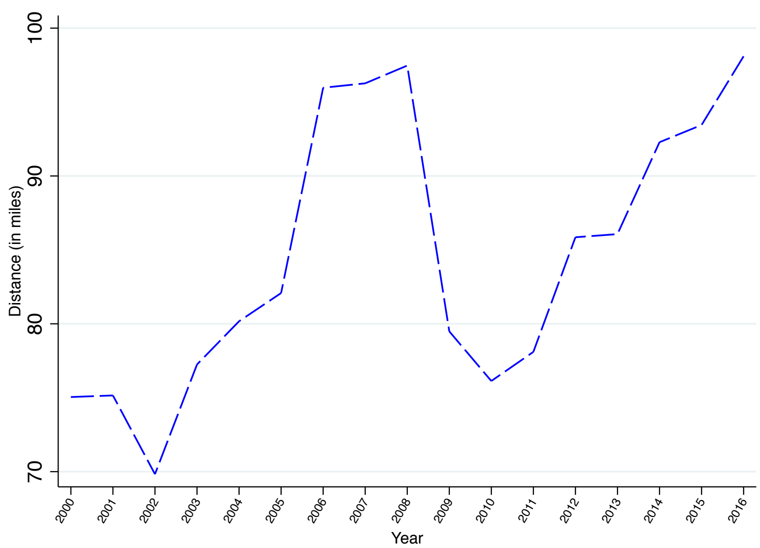


Figure 7: Distance and Lending Growth in the SBA Dataset

Figure 7 plots the estimated coefficients from a regression of the log change in the volume of SBA lending of a bank to a county on a series of interactions between lending distance and a set of dummy variable representing each year in the sample. Specifically, we plot the series of estimated coefficients β_t and associated 99% confidence intervals estimated from OLS regression of the following empirical specification: $\%\Delta SBA_{bct} = \theta_{ct} + \omega_b + \sum_t \beta_t Distance_{bct} \times Year_t + \Gamma X_{bt} + \epsilon_{bct}$, where $\%\Delta SBA_{bct}$ is the log change in the total amount of small business administration loans originated by lender b in county c and $Distance_{bct}$ is the logarithm of the average distance between the headquarters of the lender and its borrowers in the county. The shallow triangles connected by the dashed line represent the detrended GDP growth series (HP-filtered). Data for this figure is computed using the SBA dataset.

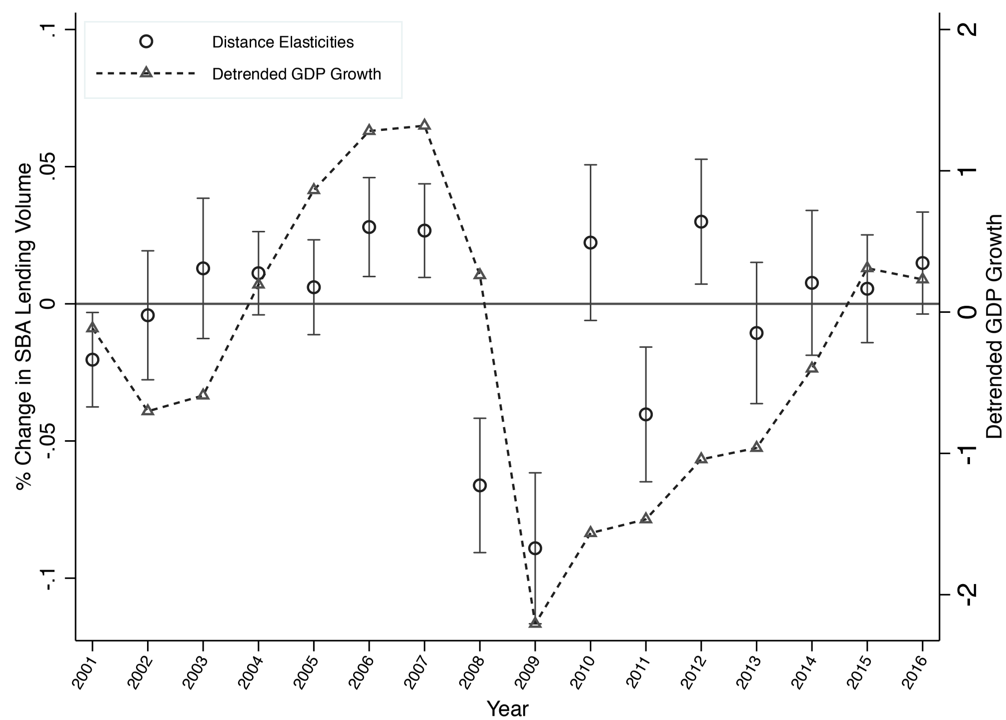


Figure 8: Distance and Likelihood of Charge-Off over the Business Cycle

Figure 8 plots the estimated coefficients from a regression of a dummy variable that takes the value of one if loan was charged-off on a series of interactions between lending distance and a set of dummy variable representing each year in the sample. Specifically, we plot the series of estimated coefficients β_t and associated 99% confidence intervals estimated from OLS regression of the following empirical specification: $CO_{bcti} = \theta_{ct} + \omega_b + \theta_i + \sum_t \beta_t Distance_{bcti} \times Year_t + \epsilon_{bcti}$, where CO_{bcti} is a dummy variable that takes the value of one if the loan was charged-off and $Distance_{bcti}$ is the logarithm of the distance between the address of the borrower and the headquarters of the lender. Data for this figure is computed using the SBA dataset.

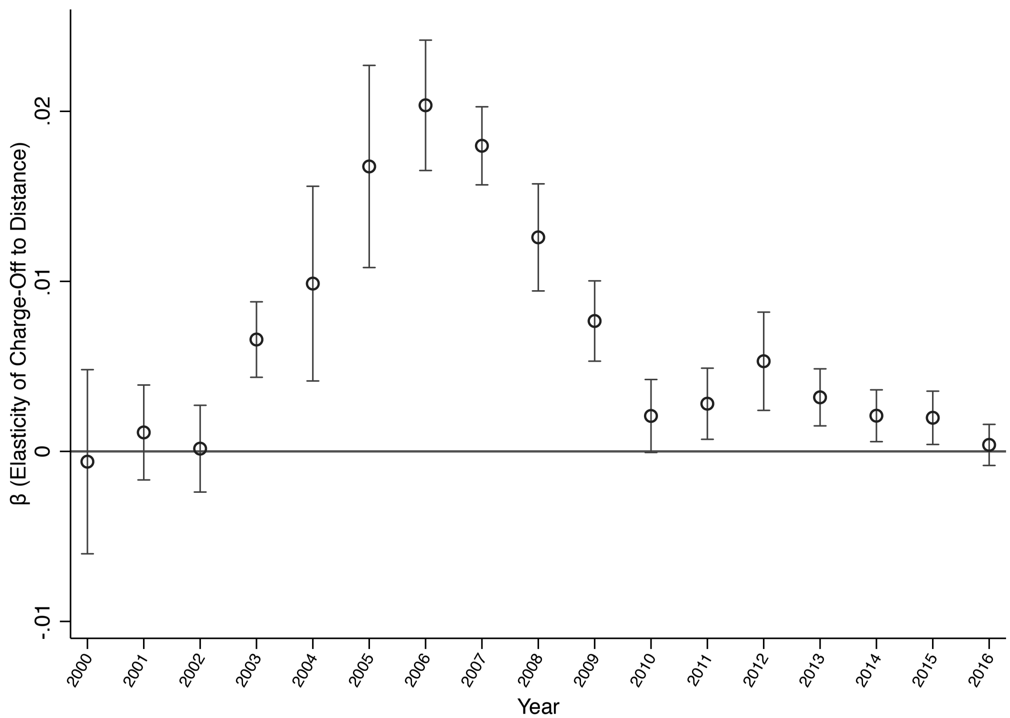


Figure 9: Distance and SBA Interest Rates over the Business Cycle

Figure 9 plots the estimated coefficients from a regression of the interest rate charged on the SBA loan on a series of interactions between lending distance and a set of dummy variables representing each year in the sample. Specifically, we plot the series of estimated coefficients β_t and associated 99% confidence intervals estimated from OLS regression of the following empirical specification: $\%IntRate_{bcti} = \theta_{ct} + \omega_b + \theta_i + \sum_t \beta_t Distance_{bcti} \times Year_t + \epsilon_{bcti}$, where $\%IntRate_{bcti}$ is the interest rate on the SBA loan and $Distance_{bcti}$ is the logarithm of the distance between the address of the borrower and the headquarters of the lender. Data for this figure is computed using the SBA dataset.

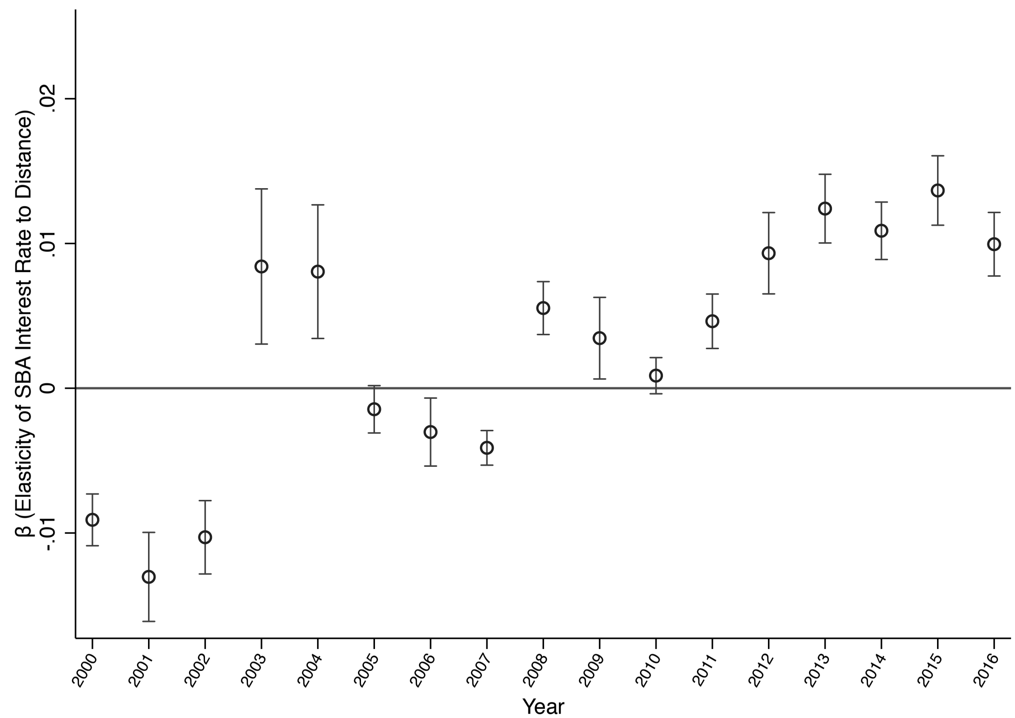
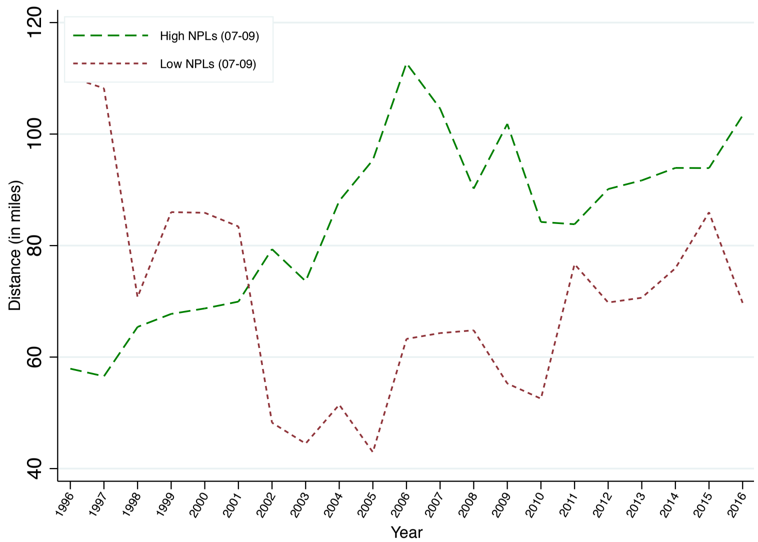


Figure 10: Lending Distances and NonPerforming Loan Ratios

Figure 10 plots the average lending distance over time after stratifying the sample of banks based on the average nonperforming loan ratio of banks over the 2007–2009 period. The figure on the left plots the equal-weighted bank distance for banks with above-median and below-median nonperforming loan ratio during the 2007–2009 period. The figure on the right plots the incremental contribution of the nonperforming loan ratio on the estimated marginal effect of distance on the log change in volume of loans. We compute the marginal effects of distance over time using estimates from the following empirical specification: $\Delta\%SBL_{bct} = \theta_{ct} + \omega_b + \sum_t \gamma_t (Distance \times Year)_{bct} + \sum_t \lambda_t (Distance \times Year \times NPL_{bt}) + \Gamma X_{bt} + \epsilon_{bct}$. The marginal effects are computed using the year-specific elasticities of loan volume with respect to distance ($\hat{\gamma}_t$) and the year-specific elasticities of loan volume with respect to distance interacted with NPL ($\hat{\lambda}_t$). Specifically, we plot $\hat{\gamma}_t + \hat{\lambda}_t \times NPL$, where $t = 1996, ...2016$, and NPL takes values $\{\mu - 2\sigma, \mu + 2\sigma\}$, where μ is the mean value of NPL over the entire sample and σ is the standard deviation of NPL. The green dashed line is the elasticity of the volume of loans over time for a representative bank with $NPLs$ two standard deviations above the mean. The solid red line is the elasticity of the volume of loans over time for a representative bank with $NPLs$ two standard deviations below the mean. Data for this figure is computed using the CRA Small Business Lending and the SOD datasets.



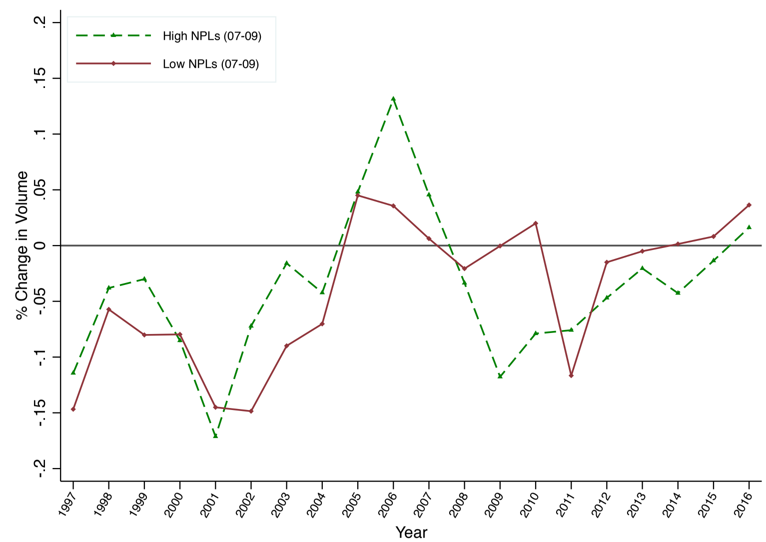


Figure 11: Lending Distances and Market Concentration

Panel A of Figure 11 plots the average lending distance over time after stratifying the sample of banks based on their level of concentration in their home markets. The figure plots the bank equal-weighted lending distance for the groups of banks with above- and below-median concentration in their home markets. Local market concentration is measured as the HHI of the small business lending market as of 1996. Panel B represents the evolution over time of estimated marginal effect of distance on changes in bank lending measured at different points of the distribution of HHI. We compute the marginal effects of distance over time using estimates from the following empirical specification: $\Delta\%SBL_{bct} = \theta_{ct} + \omega_b + \sum_t \gamma_t (Distance \times Year)_{bct} + \sum_t \lambda_t (Distance \times Year \times HHI_{bct} + \Gamma X_{bt} + \epsilon_{bct}$. The marginal effects are computed using the year-specific elasticities of loan volume with respect to distance ($\hat{\gamma}_t$) and the year-specific elasticities of loan volume with respect to distance interacted with HHI ($\hat{\lambda}_t$). Specifically, we plot $\hat{\gamma}_t + \hat{\lambda}_t \times HHI$, where $t = 1996, ...2016$, and HHI takes values $\{\mu - 2\sigma, \mu + 2\sigma\}$, where μ is the average of HHI over the entire sample and σ is the standard deviation of HHI over the entire sample. The green dashed line is the elasticity of the volume of loans over time for a representative bank-county pair whose value of HHI is two standard deviations above the mean. The solid red line is the elasticity of the volume of loans over time for a representative bank-county pair whose value of HHI is two standard deviations below the mean. Concentration is measured as the Herfindahl-Hirschmann Index in the small business lending market as of 1996. The specification includes borrower county-by-year and bank fixed-effects as well as baseline controls for natural logarithm of Total Assets, Share of Commercial & Real Estate Loans, Share of Residential Loans, and Share of Commercial & Industrial Loans. Data for this figure is computed using the CRA Small Business Lending and the SOD datasets.

Panel A: Average Distance over Time: Market Concentration

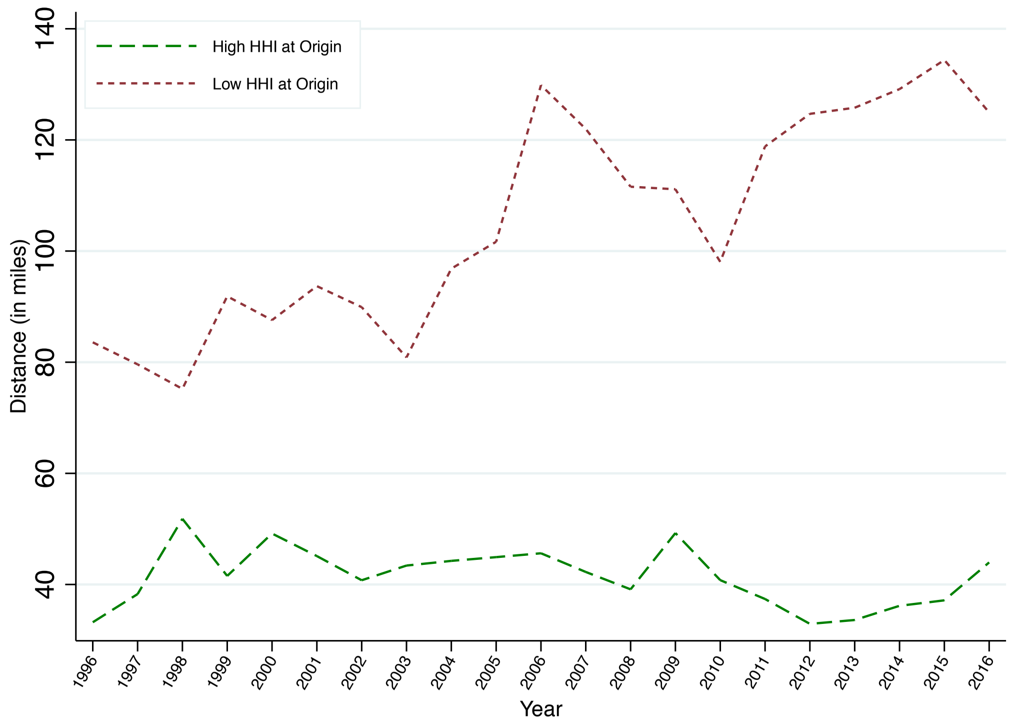
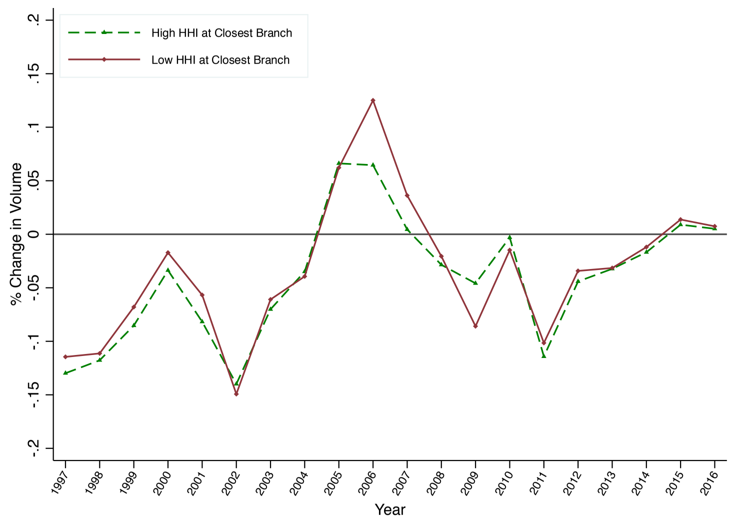


Figure 11: Lending Distances and Market Concentration (cont'd)

Panel B: Marginal Effects of Lending Distance: The Role of Market Concentration



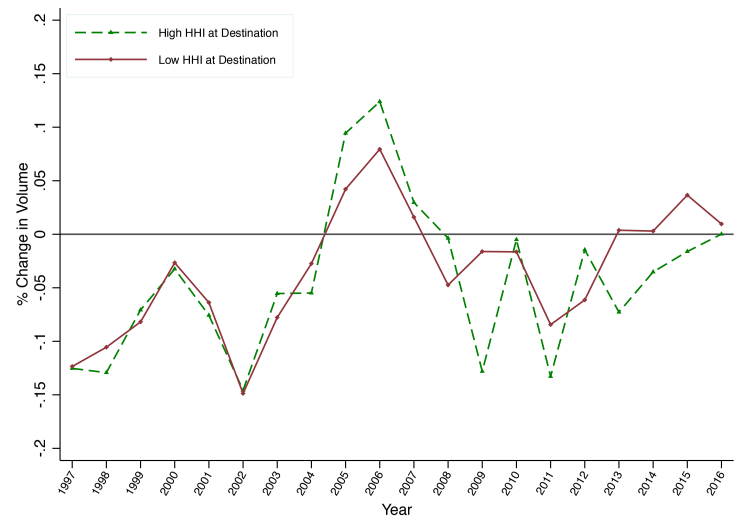


Figure 12: Local Market Concentration and Likelihood of Charge-off in the Small Business Administration Loan Dataset

Figure 12 plots the estimated coefficients from a regression of a dummy variable that takes the value of one if loan was charged-off on a series of interactions between the small business lending market concentration in the county where the borrower is located and a set of dummy variable representing each year in the sample. Specifically, we plot the series of estimated coefficients β_t and associated 99% confidence intervals estimated from OLS regression of the following empirical specification: $CO_{bcti} = \theta_t + \omega_b + \theta_i + \sum_t \beta_t HHI_c \times Year_t + \epsilon_{bcti}$, where CO_{bcti} is a dummy variable that takes the value of one if the loan was charged-off and HHI_c is the Herfindahl-Hirshmann index (HHI) of the small business lending market in the county where the borrower address is located. We compute the HHI using the same procedure we used in the main sample Data for this figure is computed using the SBA dataset.

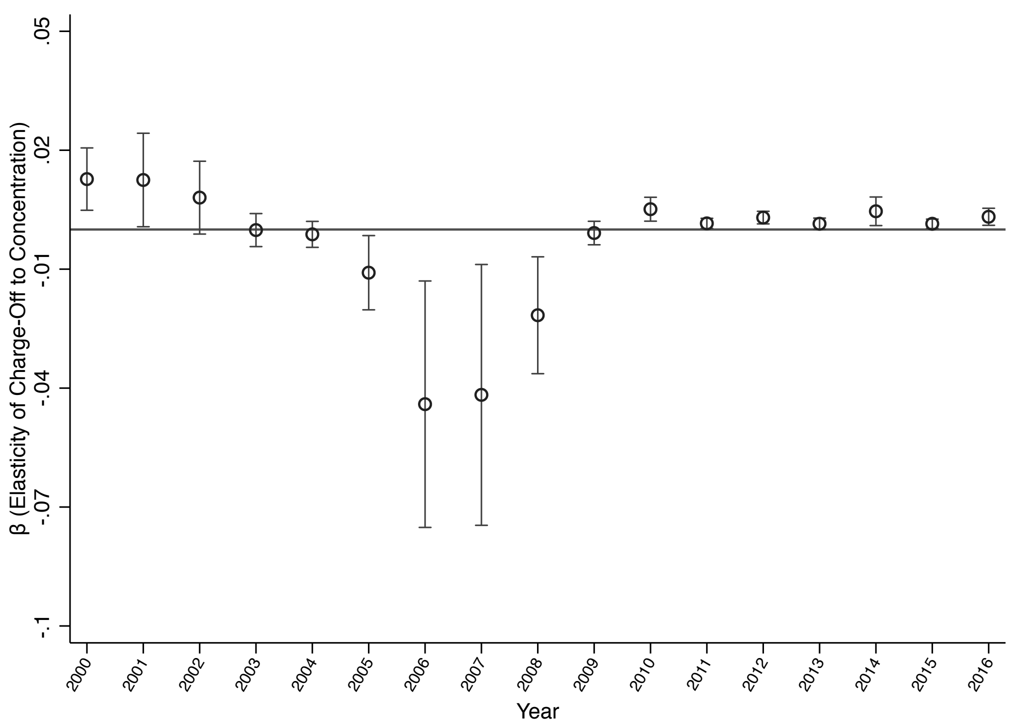


Figure 13: Bank Internal Capital Markets: Coefficient of Variation of HHI within Branch Network

Figure 13 plots the average lending distance over time after stratifying banks based on the coefficient of variation of the market concentration in counties where banks have a branch presence. The plot represents the equal-weighted bank distance for the group of banks with above- and below-median coefficient of variation in market concentration. Local market concentration is measured as the HHI of the small business lending market as of 1996. Data for this figure is computed using the CRA Small Business Lending and the SOD datasets.

Table 1: Evolution of Total Amounts of Small Business Loans by Distance Category

Panel A of Table 1 reports the total amount of small business loans originations reported in the Community Reinvestment Act (CRA) data by year in each bin representing the distance between the centroid of the borrower's county and the closest branch of the lender. The first bin represents distances between 0 and 50 miles, the second bin represents distances between 50 and 250 miles, the third bin represents distances between 250 and 1,000 miles, and the fourth bin represents borrowers and lenders that are more 1,000 miles apart. Panel B of Table 1 reports the total amount of small business administration (SBA) loans originated in each year in each bin representing the distance between the main address of the borrowerand the closest branch of the lender. The first bin represents distances between 0 and 50 miles, the second bin represents distances between 50 and 250 miles, the third bin represents distances between 250 and 1,000 miles, and the fourth bin represents borrowers and lenders that are more 1,000 miles apart.

Panel A: Volume of Small Business Loans Originations (CRA Data)

Year	TotalAmount0-50	TotalAmount50-250	TotalAmount250-1000	TotalAmount1000+	Total
1996	102,810,187	4,207,821	3,382,060	4,521,376	114,921,440
1997	130,541,771	9,011,385	7,294,432	3,658,818	150,506,400
1998	134,040,900	7,586,946	5,523,642	5,249,394	152,400,880
1999	142,967,977	9,776,986	7,919,726	7,711,816	168,376,512
2000	137,800,645	7,804,078	10,084,909	15,700,647	171,390,272
2001	182,673,269	8,627,703	12,624,184	13,999,950	217,925,104
2002	204,409,403	11,214,714	16,732,366	15,231,616	247,588,096
2003	219,894,320	13,455,397	18,986,276	16,893,891	269,229,888
2004	228,972,188	16,170,460	21,081,718	18,245,999	284,470,368
2005	207,047,621	11,563,120	25,801,432	21,508,697	265,920,864
2006	211,827,508	14,268,358	33,756,442	38,557,316	298,409,632
2007	220,991,082	18,161,007	40,876,932	44,251,324	324,280,352
2008	201,959,841	14,706,960	31,980,520	34,918,256	283,565,568
2009	151,126,509	10,545,131	15,644,679	12,350,881	189,667,200
2010	125,778,600	5,774,139	11,491,502	10,745,321	153,789,568
2011	156,682,966	7,658,716	12,984,423	13,663,029	190,989,136
2012	159,458,555	8,155,063	14,136,942	15,392,479	197,143,040
2013	166,528,022	9,207,467	12,861,050	14,120,501	202,717,040
2014	164,842,998	9,961,296	14,175,761	17,229,328	206,209,376
2015	171,910,621	10,476,532	17,022,217	18,846,757	218,256,128
2016	173,466,401	11,689,602	20,434,227	21,895,135	227,485,360

Panel B: Volume of Small Business Administration (SBA) Loans

Year	TotalAmount0-50	TotalAmount50-250	TotalAmount250-1000	TotalAmount1000+	Total
2000	3,633,314	1,466,684	1,512,078	1,218,696	7,830,772
2001	4,348,972	1,482,019	1,494,748	758,103	8,083,842
2002	5,543,095	1,847,157	1,410,184	818,440	9,618,876
2003	6,229,700	1,814,495	1,432,844	620,479	10,097,518
2004	7,305,278	2,051,545	1,707,656	701,895	11,766,374
2005	8,384,658	2,287,541	1,633,246	698,314	13,003,759
2006	7,931,796	2,007,424	1,771,869	725,878	12,436,969
2007	7,635,504	1,784,334	2,071,926	764,074	12,255,839
2008	6,365,222	1,300,046	1,529,026	723,373	9,917,666
2009	7,203,718	1,446,433	1,105,832	552,657	10,308,640
2010	12,114,943	2,045,745	1,645,449	773,776	16,579,913
2011	10,351,332	1,423,625	1,049,662	519,079	13,343,698
2012	11,202,360	1,707,601	1,479,282	791,290	15,180,532
2013	12,148,418	1,986,845	1,778,846	926,175	16,840,286
2014	13,429,151	2,176,809	2,284,627	1,294,142	19,184,728
2015	15,269,572	2,347,196	3,055,948	1,865,911	22,538,628
2016	15,273,487	2,553,234	3,515,459	1,916,885	23,259,064

Table 2: Summary Statistics

Table 2 reports summary statistics for the main variables in the empirical analysis. Δ *Volume Loans* is the log change of one plus the volume of loans originated by a bank in a county. *NPL Ratio (07-09)* is the nonperforming loan ratio of the bank during the 2007–2009 period. *HHI Destination* is the SBL market concentration in the destination (host) market. *HHI Origin* is the SBL market concentration in the closest branch (home) market. *HHI Difference* is the difference in SBL market concentration between destination (host) market and the closest branch (home) market. *Coefficient Variation HHI* is the coefficient of variation of the market concentration in counties where banks have a branch presence. Local market concentration is measured as the HHI of the small business lending market in each county measured in 1996. *I(Charge-Off = 1* is a dummy variable that takes the value of one if the loan was charged-off. *SBA Loan Interest Rate* is the initial interest rate on the SBA loan. *SBA Loan Amount* is the initial principal amount of the SBA loan. *SBA Loan Maturity* is the initial mat.

Panel A: CRA Sample

	N	Mean	St. Dev.	p10	p25	p50	p75	p90
Δ Volume Loans	5,234,549	0.135	1.985	-0.778	0	0	0	1.690
NPL Ratio (07-09)	4,235,461	0.0158	0.0122	0.00508	0.00889	0.0140	0.0206	0.0275
HHI Destination	5,220,264	295.0	668.0	18.55	51.14	132.4	308.7	633.6
HHI Origin	5,132,929	108.3	242.0	10.51	23.09	41.16	114.6	253.6
HHI Difference	5,119,738	184.4	691.2	-101.4	-3.577	55.79	221.1	529.8
Coefficient Variation HHI	3,763,276	0.874	0.427	0.376	0.610	0.872	1.085	1.308

Panel B: SBA Sample

	N	Mean	St. Dev.	p10	p25	p50	p75	p90
I(Charge-Off = 1)	1,065,304	0.146	0.353	0	0	0	0	1
SBA Loan Interest Rate	1,030,786	7.726	2.344	5.250	6	7.250	9.250	11
SBA Loan Amount	1,065,304	245.6	460.6	12.50	25.30	80	250	650
SBA Loan Maturity	1,065,304	105.1	74.21	36	60	84	120	240

Table 3: Distance and Small Business Lending: Business Cycle Indicators

Table 4 reports the coefficients of OLS regressions investigating the effect of distance on small business loan originations. Δ *Volume Loans* is the log change of one plus the volume of loans originated by a bank in a county. *HP-Filtered Real GDP* is the standardized HP-filtered percent change in the real GDP. Real GDP series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. Δ *Ln(Unempld Rate)* is standardized log difference in the US annual unemployment rate. The unemployment rate series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Spreads* is the standardized net percentage of domestic banks increasing spreads of loan rates over banks' cost of funds to small firms. The series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Ln(Distance)* is the natural logarithm of the minimum distance between the bank's branches and the county centroid. The specification includes borrower county-by-year and bank fixed-effects as well as baseline controls for natural logarithm of Total Assets, Share of Commercial & Real Estate Loans, Share of Residential Loans, and Share of Commercial & Industrial Loans. Standard errors are presented in parentheses, and are clustered at the level of the county. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	Δ Volume Loans		
Ln(Distance)	-0.038***	-0.038***	-0.038***
	(0.001)	(0.001)	(0.001)
Ln(Distance) × HP-Filtered Real GDP	0.035***		
	(0.001)		
Ln(Distance) × Δ Ln(Unempld Rate)		-0.018***	
		(0.000)	
Ln(Distance) × Spreads			-0.017***
			(0.000)
Observations	5234549	5234549	5234549
Adjusted R^2	0.017	0.017	0.017
Baseline Controls	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes
Borrower County-Year Fixed Effects	Yes	Yes	Yes

Table 4: Distance and Small Business Lending: Size Categories

Table 4 reports the coefficients of OLS regressions investigating the effect of distance on small business loan originations on three partitions of bank size. Δ *Volume Loans* is the log change of one plus the volume of loans originated by a bank in a county. *HP-Filtered Real GDP* is the standardize HP-filtered percent change in the real GDP. Real GDP series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. Δ *Ln(Unempld Rate)* is standardized log difference in the US annual unemployment rate. The unemployment rate series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Spreads* is the standardized net percentage of domestic banks increasing spreads of loan rates over banks' cost of funds to small firms. The series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Ln(Distance)* is the natural logarithm of the minimum distance between the bank's branches and the county centroid. The specification includes borrower county-by-year and bank fixed-effects as well as baseline controls for natural logarithm of Total Assets, Share of Commercial & Real Estate Loans, Share of Residential Loans, and Share of Commercial & Industrial Loans. Standard errors are presented in parentheses, and are clustered at the level of the county. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Δ Volume Loans								
	$\leq$ \$10bi	[\$10bi,\$50bi]	>\$50bi	$\leq$ \$10bi	[\$10bi,\$50bi]	>\$50bi	$\leq$ \$10bi	[\$10bi,\$50bi]	>\$50bi
Ln(Distance)	-0.048***	-0.053***	-0.011***	-0.046***	-0.050***	-0.012***	-0.046***	-0.050***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Distance) × HP-Filtered Real GDP	0.041***	0.043***	0.021***						
	(0.001)	(0.001)	(0.001)						
Ln(Distance) × Δ Ln(Unempld Rate)				-0.032***	-0.024***	-0.004***			
				(0.001)	(0.001)	(0.001)			
Ln(Distance) × Spreads							-0.033***	-0.008***	-0.004***
							(0.001)	(0.001)	(0.001)
Observations	3211384	1000682	1022464	3211384	1000682	1022464	3211384	1000682	1022464
Adjusted R^2	0.021	0.017	0.028	0.020	0.017	0.027	0.020	0.017	0.027
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower County-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Distance and Small Business Lending: Small Agricultural Loans

Table 5 reports the coefficients of OLS regressions investigating the effect of distance on small farm loan originations. The dependent variable, Δ *Volume Farm Loans*, is the log change of one plus the volume of small farm loans originated by a bank to farmers in each county. *HP-Filtered Real GDP* is the standardized HP-filtered percent change in the real GDP. Real GDP series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. Δ *Ln(Unempld Rate)* is standardized log difference in the US annual unemployment rate. The unemployment rate series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Spreads* is the standardized net percentage of domestic banks increasing spreads of loan rates over banks' cost of funds to small firms. The series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Ln(Distance)* is the natural logarithm of the minimum distance between the bank's branches and the county centroid. The specification includes borrower county-by-year and bank fixed-effects as well as baseline controls for natural logarithm of Total Assets, Share of Commercial & Real Estate Loans, Share of Residential Loans, and Share of Commercial & Industrial Loans. Standard errors are presented in parentheses, and are clustered at the level of the county. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	Δ Volume Farm Loans		
Ln(Distance)	-0.018***	-0.018***	-0.018***
	(0.001)	(0.001)	(0.001)
Ln(Distance) × HP-Filtered Real GDP	0.019***		
	(0.001)		
Ln(Distance) × Δ Ln(Unempld Rate)		-0.004***	
		(0.001)	
Ln(Distance) × Spreads			-0.009***
			(0.001)
Observations	1563898	1563898	1563898
Adjusted R^2	0.011	0.011	0.011
Baseline Controls	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes
Borrower County-Year Fixed Effects	Yes	Yes	Yes

Table 6: Distance and Small Business Administration Lending: Business Cycle Indicators

Table 6 reports the coefficients of OLS regressions investigating the effect of distance on originations of small business administration guaranteed loans. The dependent variable, Δ *Volume Loans* is the log change of one plus the volume of loans originated by a bank in a county. *HP-Filtered Real GDP* is the standardize HP-filtered percent change in the real GDP. Real GDP series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. Δ *Ln(Unempld Rate)* is standardized log difference in the US annual unemployment rate. The unemployment rate series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Spreads* is the standardized net percentage of domestic banks increasing spreads of loan rates over banks' cost of funds to small firms. The series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Ln(Distance)* represents the logarithm of the average distance between the headquarters of a bank and its borrowers in the county. Standard errors are presented in parentheses, and are clustered at the level of the county. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	Δ Volume Loans		
Ln(Distance)	-0.000	-0.001	-0.002
	(0.003)	(0.003)	(0.003)
Ln(Distance) $\times$ HP-Filtered Real GDP	0.016***		
	(0.002)		
Ln(Distance) $\times$ Δ Ln(Unempld Rate)		-0.023***	
		(0.002)	
Ln(Distance) $\times$ Spreads			-0.022***
			(0.002)
Observations	104742	104742	104742
Adjusted R^2	0.021	0.022	0.022
Baseline Controls	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes
Borrower County-Year Fixed Effects	Yes	Yes	Yes

Table 7: Distance and Small Business Lending: NonPerforming Loan Ratio

Table 7 reports the coefficients of OLS regressions investigating whether the relation between lending distance and the business cycle is more or less pronounced for lenders that experienced greater loan delinquency ratios during the financial crisis (07–09). Δ *Volume Loans* is the log change of one plus the volume of loans originated by a bank in a county. *HP-Filtered Real GDP* is the standardize HP-filtered percent change in the real GDP. Real GDP series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. Δ *Ln(Unempld Rate)* is standardized log difference in the US annual unemployment rate. The unemployment rate series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Spreads* is the standardized net percentage of domestic banks increasing spreads of loan rates over banks' cost of funds to small firms. The series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Ln(Distance)* is the natural logarithm of the minimum distance between the bank's branches and the county centroid. *NPL Ratio (07-09)* is the nonperforming loan ratio of the bank during the 2007–2009 period. The specification includes borrower county-by-year and bank fixed-effects as well as baseline controls for natural logarithm of Total Assets, Share of Commercial & Real Estate Loans, Share of Residential Loans, and Share of Commercial & Industrial Loans. The specification also conditions on the interactions between NPL Ratio and the business cycle indicators, and NPL Ratio and Distance. Standard errors are presented in parentheses, and are clustered at the level of the county. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	Δ Volume Loans		
Ln(Distance)	-0.035***	-0.035***	-0.036***
	(0.000)	(0.001)	(0.001)
Ln(Distance) × HP-Filtered Real GDP	0.027***		
	(0.001)		
Ln(Distance) × HP-Filtered Real GDP × NPL Ratio (07-09)	0.002***		
	(0.001)		
Ln(Distance) × Δ Ln(Unempld Rate)		-0.019***	
		(0.001)	
Ln(Distance) × Δ Ln(Unempld Rate) × NPL Ratio (07-09)		-0.002***	
		(0.001)	
Ln(Distance) × Spreads			-0.019***
			(0.000)
Ln(Distance) × Spreads × NPL Ratio (07-09)			-0.004***
			(0.001)
Observations	4235461	4235461	4235461
Adjusted R^2	0.011	0.011	0.011
Baseline Controls	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes
Borrower County-Year Fixed Effects	Yes	Yes	Yes

Table 8: Bank Level Analysis: Tail Risks and Distance Cyclicality

Panel A of Table 8 reports summary statistics of the main variables used in the bank-level analysis of distance cyclicality and stock-return based measures of tail risks. Panel B reports the coefficients of OLS regressions investigating the relation between distance cyclicality and tail risks. The dependent variables, *Return Bad Bank Days* and *Return Bad Market Days*, are the average bad-day returns of each bank calculated from bad days between September 1, 2007, and October 1, 2010. Bad Bank days are 5% of days from July 1926 to July 2015 with the lowest value-weighted return for the Fama/French banking industry portfolio and Bad Market days are 5% of days from July 1926 to July 2015 with the lowest CRSP value-weighted market index return (NYSE, AMEX, NASDAQ & ARCA). $\rho(GDP, Dist)$ is the coefficient of correlation between the average distance between the lender and its respective borrowers in a given year and the HP-filtered percent change in the real GDP. Real GDP series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. $\rho(Unemployment, Dist)$ is the coefficient of correlation between the average distance between the lender and its respective borrowers in a given year and the log difference in the US annual unemployment rate. The unemployment rate series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. $\rho(Spreads, Dist)$ is the coefficient of correlation between the average distance between the lender and its respective borrowers in a given year and the net percentage of domestic banks increasing spreads of loan rates over banks' cost of funds to small firms. The series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. We use a balanced sample of banks for which we observations on distance throughout the entire period. All specifications include fixed effects based on the size-bins that the bank falls into. All banks are divided into 10 size buckets based on their total assets. Standard errors are presented in parentheses, and are robust to heteroskedasticity. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: Summary Statistics

	N	Mean	St. Dev.	p10	p25	p50	p75	p90
Av. Ret. on Bad Bank Days	103	-0.0333	0.0114	-0.0491	-0.0402	-0.0332	-0.0282	-0.0215
Av. Ret. on Bad Market Days	103	-0.0389	0.0122	-0.0533	-0.0463	-0.0394	-0.0338	-0.0260
$\rho(GDP, Dist)$	103	0.0607	0.260	-0.279	-0.129	0.0719	0.266	0.398
$\rho(Unemployment, Dist)$	103	-0.0107	0.251	-0.290	-0.163	-0.0637	0.126	0.297
$\rho(Spreads, Dist)$	103	-0.0229	0.257	-0.302	-0.225	-0.0464	0.132	0.369

Panel B: OLS Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	Return Bad Bank Days			Return Bad Market Days		
$\rho(GDP, Dist)$	-0.010***			-0.010**		
	(0.004)			(0.004)		
$\rho(Unemployment, Dist)$		0.007**			0.009**	
		(0.003)			(0.004)	
$\rho(Spreads, Dist)$			0.005			0.007**
			(0.003)			(0.003)
Observations	103	103	103	103	103	103
Adjusted R^2	0.456	0.426	0.413	0.323	0.309	0.296
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Distance and Small Business Lending: The Role of Market Concentration

Table 9 reports the coefficients of OLS regressions investigating the role that market concentration plays in the relation between lending distance and the business cycle. The dependent variable, Δ *Volume Loans* is the log change of one plus the volume of loans originated by a bank in a county. *HP-Filtered Real GDP* is the standardize HP-filtered percent change in the real GDP. Real GDP series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. Δ *Ln(Unempld Rate)* is standardized log difference in the US annual unemployment rate. The unemployment rate series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Spreads* is the standardized net percentage of domestic banks increasing spreads of loan rates over banks' cost of funds to small firms. The series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Ln(Distance)* is the natural logarithm of the minimum distance between the bank's branches and the county centroid. *HHI Difference* is the difference in SBL market concentration between destination (host) market and the closest branch (home) market. *HHI Origin* is the SBL market concentration in the closest branch (home) market. *HHI Destination* is the SBL market concentration in the destination (host) market. Local market concentration is measured as the HHI of the small business lending market in each county measured in 1996. The specification includes borrower county-by-year and bank fixed-effects as well as baseline controls for natural logarithm of Total Assets, Share of Commercial & Real Estate Loans, Share of Residential Loans, and Share of Commercial & Industrial Loans. The specification also conditions on the interactions between HHI and the business cycle indicators, and HHI and Distance. Standard errors are presented in parentheses, and are clustered at the level of the county. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Δ Volume Loans								
Ln(Distance)	-0.038***	-0.037***	-0.038***	-0.038***	-0.037***	-0.037***	-0.038***	-0.038***	-0.038***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Distance) × HP-Filtered Real GDP	0.036***	0.035***	0.035***						
	(0.001)	(0.001)	(0.001)						
Ln(Distance) × HP-Filtered Real GDP × HHI Destination	0.006***								
	(0.001)								
Ln(Distance) × HP-Filtered Real GDP × HHI Origin		-0.007***							
		(0.001)							
Ln(Distance) × HP-Filtered Real GDP × HHI Difference			0.008***						
			(0.001)						
Ln(Distance) × Δ Ln(Unempld Rate)				-0.018***	-0.018***	-0.018***			
				(0.000)	(0.000)	(0.000)			
Ln(Distance) × Δ Ln(Unempld Rate) × HHI Destination				-0.002***					
				(0.000)					
Ln(Distance) × Δ Ln(Unempld Rate) × HHI Origin					0.006***				
					(0.001)				
Ln(Distance) × Δ Ln(Unempld Rate) × HHI Difference						-0.005***			
						(0.001)			
Ln(Distance) × Spreads							-0.017***	-0.016***	-0.016***
							(0.000)	(0.000)	(0.000)
Ln(Distance) × Spreads × HHI Destination							-0.001**		
							(0.000)		
Ln(Distance) × Spreads × HHI Origin								0.001***	
								(0.000)	
Ln(Distance) × Spreads × HHI Difference									-0.001*
									(0.000)
Observations	5220264	5132929	5119738	5220264	5132929	5119738	5220264	5132929	5119738
Adjusted R^2	0.017	0.018	0.018	0.017	0.017	0.017	0.017	0.017	0.017
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower County-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Distance and Small Business Lending: The Role of Internal Capital Markets

Table 10 reports the coefficients of OLS regressions investigating the role that internal capital markets play in the relation between lending distance and the business cycle. The dependent variable, Δ *Volume Loans*, is the log change in the volume of loans originated by a bank in a county. *HP-Filtered Real GDP* is the standardize HP-filtered percent change in the real GDP. Real GDP series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. Δ *Ln(Unempld Rate)* is standardized log difference in the US annual unemployment rate. The unemployment rate series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Spreads* is the standardized net percentage of domestic banks increasing spreads of loan rates over banks' cost of funds to small firms. The series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Ln(Distance)* is the natural logarithm of the minimum distance between the bank's branches and the county centroid. *Coefficient Variation HHI* is the coefficient of variation of the market concentration in counties where banks have a branch presence. Local market concentration is measured as the HHI of the small business lending market as of 1996. The specification includes borrower county-by-year and bank fixed-effects as well as baseline controls for natural logarithm of Total Assets, Share of Commercial & Real Estate Loans, Share of Residential Loans, and Share of Commercial & Industrial Loans. The specification also conditions on the interactions between Std. Dev. HHI and the business cycle indicators, and Std. Dev. HHI and Distance. Standard errors are presented in parentheses, and are clustered at the level of the county. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	Δ Volume Loans		
Ln(Distance)	-0.042***	-0.041***	-0.041***
	(0.001)	(0.001)	(0.001)
Ln(Distance) × HP-Filtered Real GDP	0.018***		
	(0.001)		
Ln(Distance) × HP-Filtered Real GDP × Coefficient Variation HHI	-0.026***		
	(0.001)		
Ln(Distance) × Δ Ln(Unempld Rate)		-0.005***	
		(0.001)	
Ln(Distance) × Δ Ln(Unempld Rate) × Coefficient Variation HHI		0.026***	
		(0.001)	
Ln(Distance) × Spreads			-0.015***
			(0.001)
Ln(Distance) × Spreads × Coefficient Variation HHI			0.025***
			(0.001)
Observations	3763276	3763276	3763276
Adjusted R^2	0.019	0.019	0.019
Baseline Controls	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes
Borrower County-Year Fixed Effects	Yes	Yes	Yes

Table 11: Robustness: Interstate Banking Deregulation

Table 11 reports the coefficients of OLS regressions investigating how the time elapsed since the interstate banking deregulation mediates the relation between lending distance and the business cycle. Δ *Volume Loans* is the log change in the volume of loans originated by a bank in a county. *HP-Filtered Real GDP* is the standardized HP-filtered percent change in the real GDP. Real GDP series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. Δ *Ln(Unempld Rate)* is standardized log difference in the US annual unemployment rate. The unemployment rate series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Spreads* is the standardized net percentage of domestic banks increasing spreads of loan rates over banks' cost of funds to small firms. The series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Ln(Distance)* is the natural logarithm of the minimum distance between the bank's branches and the county centroid. *Yrs. since M&A Dereg. Destination* is the natural logarithm of the difference between 1996 and the year of adoption of interstate banking deregulation in each state where the borrower is located. *Yrs. since M&A Dereg. Origin* is the natural logarithm of the difference between 1996 and the year of adoption of interstate banking deregulation in the state where the closest branch (home) market is located. Standard errors are presented in parentheses, and are clustered at the level of the county. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
			Δ Volume Loans			
Ln(Distance)	-0.044***	-0.012***	-0.043***	-0.014***	-0.044***	-0.015***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Ln(Distance) × HP-Filtered Real GDP	0.084***	0.015***				
	(0.005)	(0.004)				
Ln(Distance) × HP-Filtered Real GDP × Yrs. since M&A Dereg. Destination	-0.022***					
	(0.002)					
Ln(Distance) × HP-Filtered Real GDP × Yrs. since M&A Dereg. Origin		0.009***				
		(0.002)				
Ln(Distance) × Δ Ln(Unempld Rate)			-0.031***	0.005		
			(0.004)	(0.004)		
Ln(Distance) × Δ Ln(Unempld Rate) × Yrs. since M&A Dereg. Destination			0.006***			
			(0.002)			
Ln(Distance) × Δ Ln(Unempld Rate) × Yrs. since M&A Dereg. Origin				-0.010***		
				(0.002)		
Ln(Distance) × Spreads					-0.027***	-0.024***
					(0.004)	(0.004)
Ln(Distance) × Spreads × Yrs. since M&A Dereg. Destination					0.005***	
					(0.002)	
Ln(Distance) × Spreads × Yrs. since M&A Dereg. Origin						0.003**
						(0.002)
Observations	5217323	5231569	5217323	5231569	5217323	5231569
Adjusted R^2	0.018	0.018	0.017	0.017	0.017	0.017
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Borrower County-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 12: Robustness: Large Bank Penetration in the County

Table 12 reports the coefficients of OLS regressions investigating the role that an increase in the presence by a large bank in a county plays in the relation between lending distance and the business cycle. Δ *Volume Loans* is the log change in the volume of loans originated by a bank in a county. *HP-Filtered Real GDP* is the standardized HP-filtered percent change in the real GDP. Real GDP series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. Δ *Ln(Unempld Rate)* is standardized log difference in the US annual unemployment rate. The unemployment rate series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Spreads* is the standardized net percentage of domestic banks increasing spreads of loan rates over banks' cost of funds to small firms. The series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Ln(Distance)* is the natural logarithm of the minimum distance between the bank's branches and the county centroid. Δ *Share Large Banks > 5% (Destination)* is an indicator variable that takes the value of one if a large banking organization (bank whose total assets exceed $50 billion) increases its share of deposits in the destination county by more than 5% in the preceding year. Δ *Share Large Banks > 5% (Origin)* is an indicator variable that takes the value of one if a large banking organization (bank whose total assets exceed $50 billion) increases its share of deposits in the home (origin) county by more than 5% in the preceding year. We excluded the large bank observations that originated the shock. Therefore, we exclude the lending in the county by the large bank itself. Standard errors are presented in parentheses, and are clustered at the level of the county. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Volume Loans					
Ln(Distance)	-0.040***	-0.043***	-0.040***	-0.044***	-0.040***	-0.045***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Distance) × HP-Filtered Real GDP	0.038***	0.019***				
	(0.001)	(0.001)				
Ln(Distance) × HP-Filtered Real GDP × Δ Share Large Banks > 5% (Destination)	-0.019***					
	(0.003)					
Ln(Distance) × HP-Filtered Real GDP × Δ Share Large Banks > 5% (Origin)		0.059***				
		(0.002)				
Ln(Distance) × Δ Ln(Unempld Rate)			-0.019***	-0.012***		
			(0.001)	(0.001)		
Ln(Distance) × Δ Ln(Unempld Rate) × Δ Share Large Banks > 5% (Destination)			0.008***			
			(0.003)			
Ln(Distance) × Δ Ln(Unempld Rate) × Δ Share Large Banks > 5% (Origin)				-0.032***		
				(0.002)		
Ln(Distance) × Spreads					-0.017***	-0.016***
					(0.000)	(0.001)
Ln(Distance) × Spreads × Δ Share Large Banks > 5% (Destination)					-0.002	
					(0.003)	
Ln(Distance) × Spreads × Δ Share Large Banks > 5% (Origin)						-0.012***
						(0.002)
Observations	5173063	5197133	5173063	5197133	5173063	5197133
Adjusted R^2	0.018	0.019	0.017	0.017	0.017	0.017
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Borrower County-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Online Appendix for Going the Extra Mile: Distant Lending and Credit Cycles

June 26th, 2019

1 Table of Contents:

Figure IA.1: Effects of Distance on Credit Growth over the Business Cycle (Alternative Dependent Variables

Figure IA.1 plots the year-specific semi-elasticities of an increase in the lending distance on the growth in small business lending using alternative dependent variables. The top figure represents the estimated coefficients from a regression of the log change in the number of small business loans to borrowers in a county on a series of interactions between lending distance and a set of dummy variable representing each year in the sample. Specifically, we plot the series of estimated coefficients β_t and associated confidence intervals in the regression $\%\Delta Nbr.SBL_{bct} = \theta_{ct} + \omega_b + \sum_t \beta_t Distance_{bct} \times Year_t + \Gamma X_{bt} + \epsilon_{bct}$. The bottom figure represents the estimated coefficients from a regression of an indicator variable that takes the value of one if the bank made a loan to a borrower located in a county where the bank had not made loans the previous year on a series of interactions between lending distance and a set of dummy variable representing each year in the sample. Specifically, we plot the series of estimated coefficients β_t and associated confidence intervals in the regression $Start_{bct} = \theta_{ct} + \omega_b + \sum_t \beta_t Distance_{bct} \times Year_t + \Gamma X_{bt} + \epsilon_{bct}$. The shallow triangles connected by the dashed line represent the detrended GDP growth series (HP-filtered) Data for this figure is computed using the CRA Small Business Lending and the SOD datasets.

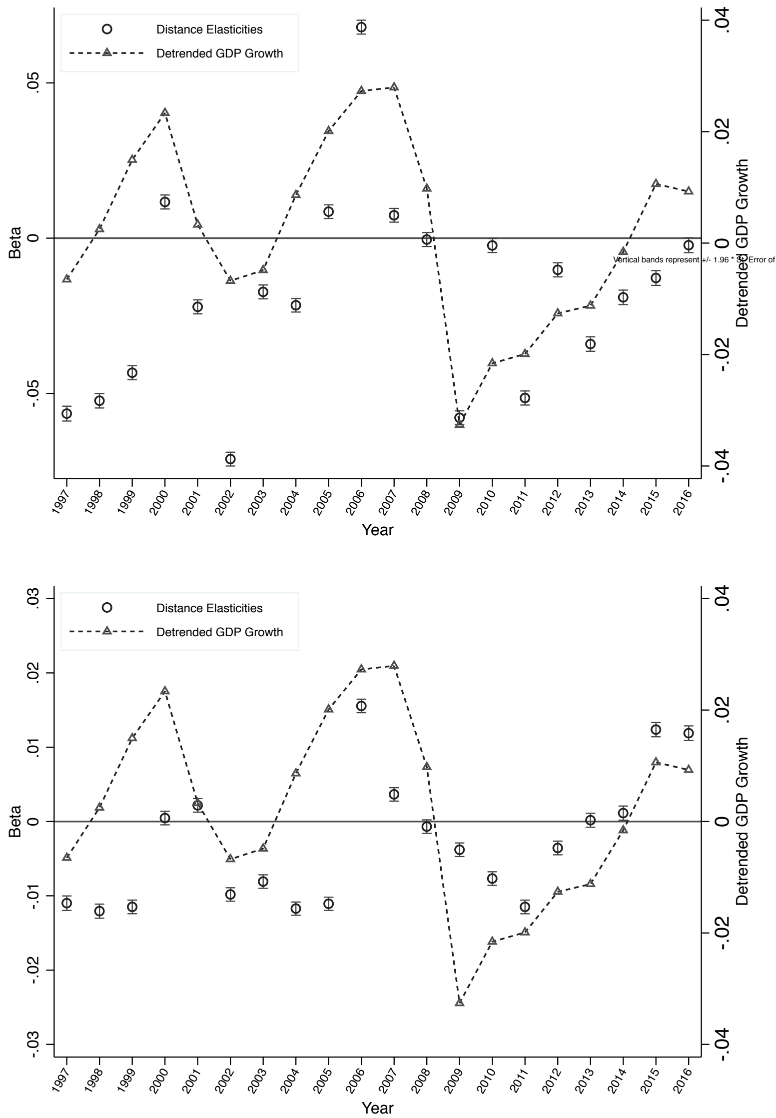


Figure IA.2: Distance after purging the effects of M&As

Figure IA.2 plots the average weighted lending distance after purging the potential effects of M&As. Lending Distance for each loan is computed as the geodetic distance between the borrower's county centroid and its respective lender closest branch. The top figure plots average distance after eliminating from the sample all banks that were the target of an acquisition. The bottom figure plots the average lending distance for a sample of pro-forma banks, i.e. after adjusting the lending of each surviving bank in the sample by including all loans of all banks that they acquired prior to 2016. In this analysis, the lending distance of each pro-forma bank in each county is computed as the minimum distance that the pro-forma had to the county over the entire period.

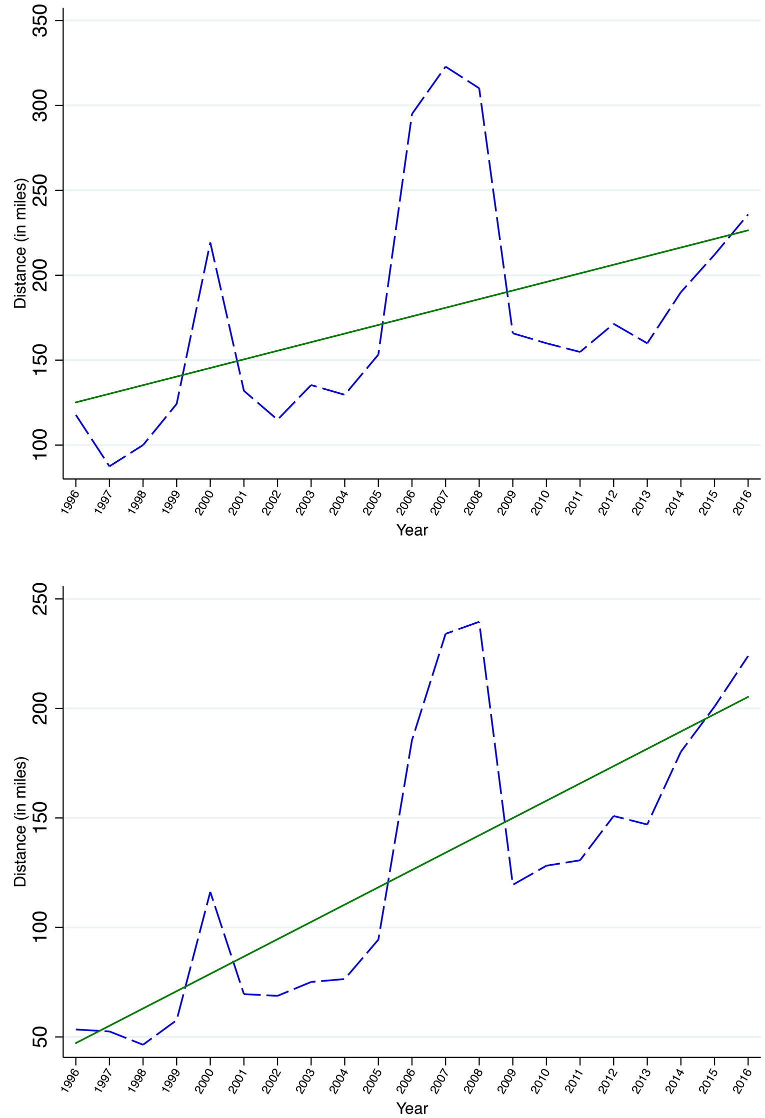


Figure IA.3: Robustness: Evolution of Lending Distances (Distances to Population-Weighted County Centroid

Figure IA.3 plots the time-series of the average weighted lending distance between lender and borrowers in the dataset. Lending Distance for each loan is computed as the geodetic distance between the borrower's *population-weighted* county centroid and its respective lender closest branch.

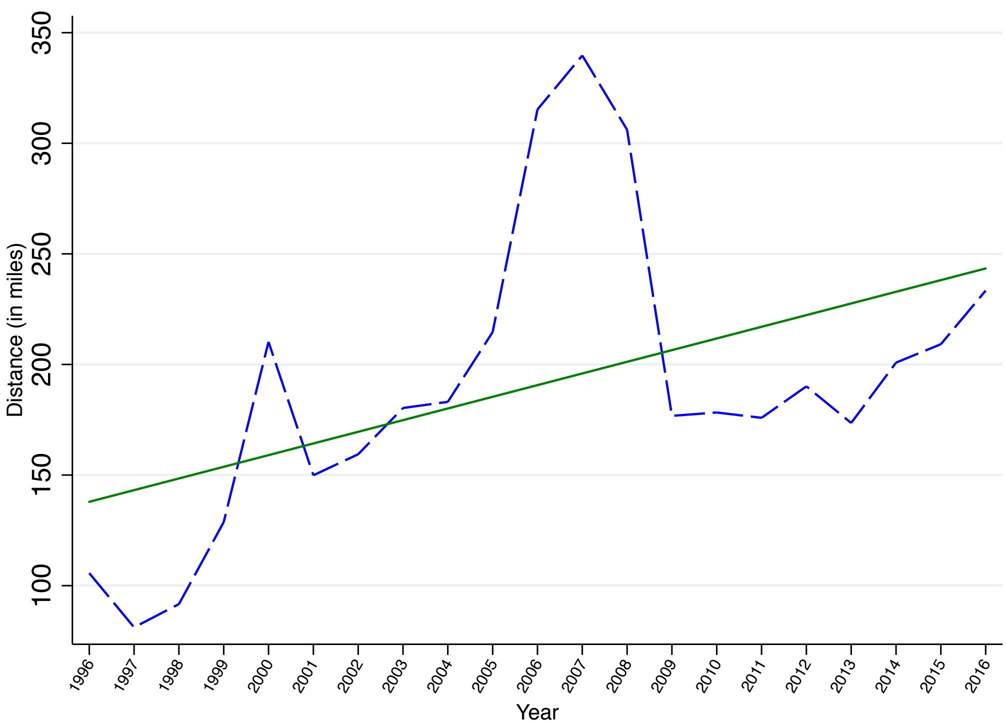


Figure IA.4: Effect of Distance on Likelihood of Charge-Off by Type of SBA Program

Figure IA.4 plots the estimated year-specific semi-elasticities between the likelihood of charge-off of a SBA loan in each SBA program type and an increase in the lending distance between a bank and a borrower. The plot represents a series of estimated coefficients of a regression of the likelihood of loan charge-off on the interaction of lending distance and a set of dummy variable representing each year in the sample. Specifically, we plot (β_t) from estimating the following specification: $\%CO_{bcti} = \theta_{ct} + \omega_b + \theta_i + \sum_t \beta_t Distance_{bcti} \times Year_t + \epsilon_{bcti}$ and the vertical bands present 99% confidence intervals for the point estimates in each year. The shallow red circles represent the coefficients for SBA loans originated under the SBA XPRESS program. The shallow green triangles represent the coefficients for SBA loans originated under the Regular 7(a) program.

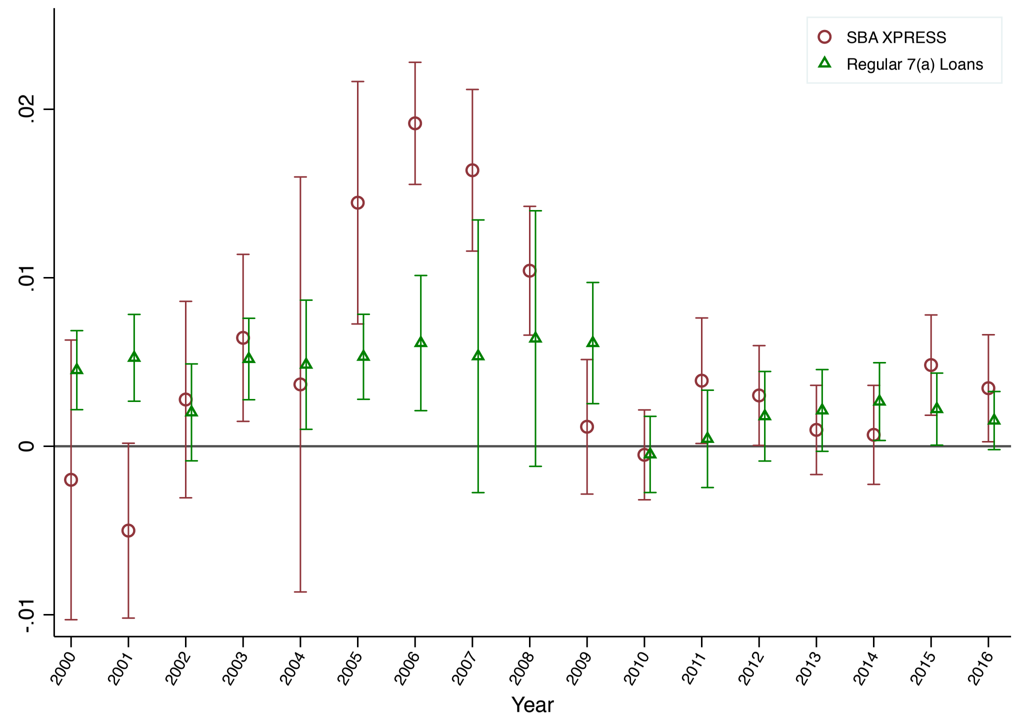


Figure IA.5: Internal Capital Markets (Coefficient of Variation in Areas with low and High HHI)

Figure IA.5 plots the average lending distance over time after stratifying banks based on the coefficient of variation of the market concentration in counties where banks have a branch presence and further partitioning the subset of banks with low coefficient of variation between banks exposed to above- and below-median market concentration in the local markets of their branch network. The figure plots the equal-weighted bank distance for the groups of banks with above-median coefficient of variation of market concentration; below-median coefficient of variation and below-median HHI; and below-median coefficient of variation and above-median HHI Local market concentration is measured as the HHI of the small business lending market as of 1996. Data for this figure is computed using the CRA Small Business Lending and the SOD datasets.

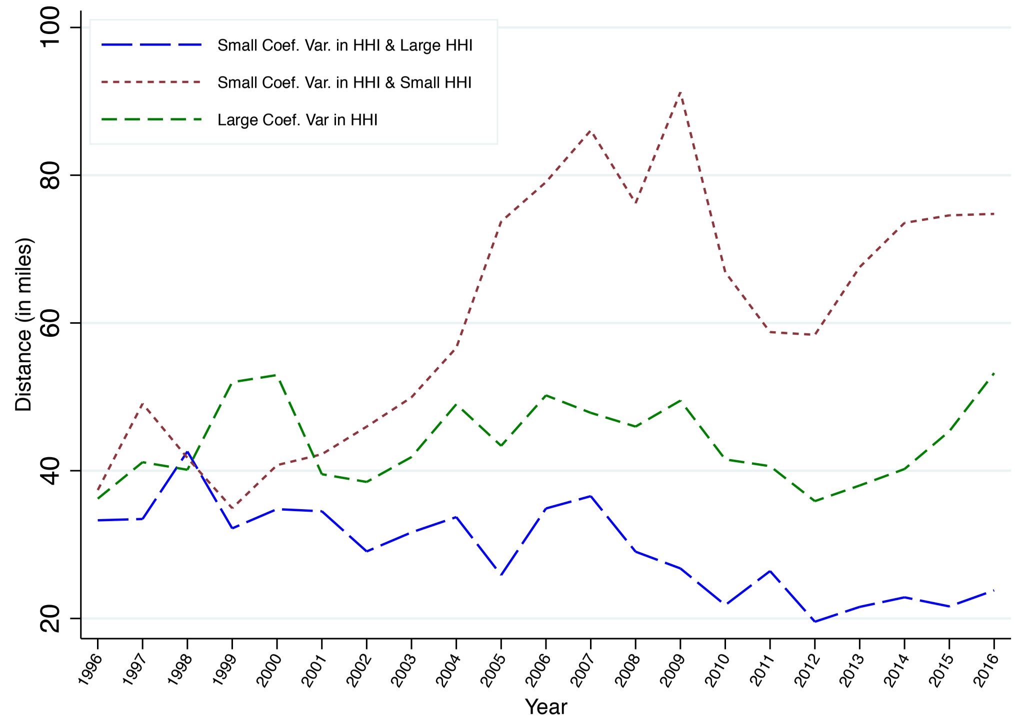


Figure IA.6: Robustness: Histogram of Estimated Coefficients of Distance and GDP Interaction after Excluding One State at a Time)

Figure IA.6 plots the estimated coefficients on the interaction between borrower-lender distance indicator and the GDP indicator after excluding one state at a time in the following specification: $\%\Delta SBA_{bct} = \theta_{ct} + \omega_b + \sum_t \beta_t Distance_{bct} \times Z_t + \Gamma X_{bt} + \epsilon_{bct}$, where $\%\Delta SBA_{bct}$ is the log change in the total amount of small business administration loans originated by lender b in county c, $Distance_{bct}$ is the logarithm of the average distance between the headquarters of the lender and its borrowers in the county, and Z_t is the standardized HP-filtered percent change in the real GDP.

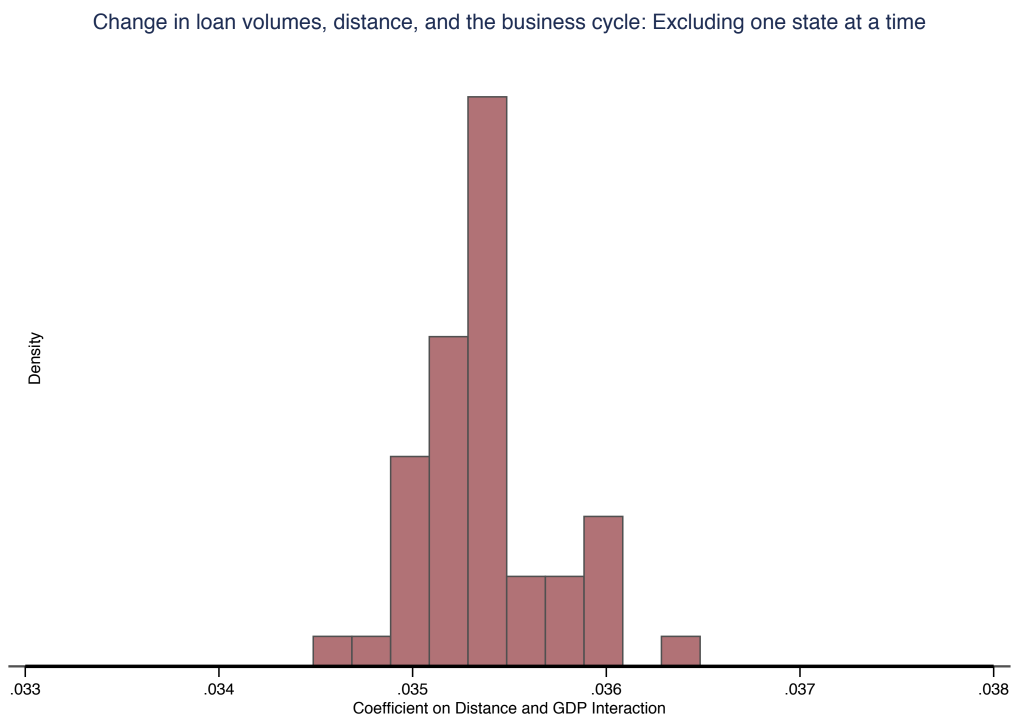


Figure IA.7: Robustness: Alternative Measure of Distance in the Small Business Administration Sample

Figure IA.7 plots the effect of distance between the borrower and lender in the SBA dataset over time. To compute distances, we hand-match all lenders with more that 500 SBA loans to the Summary of Deposits dataset and we compute distance as the minimum distance between the borrowers' address and their respective lender closest branch. The plot shows the same boom-bust pattern in average distance around the recent financial crisis.

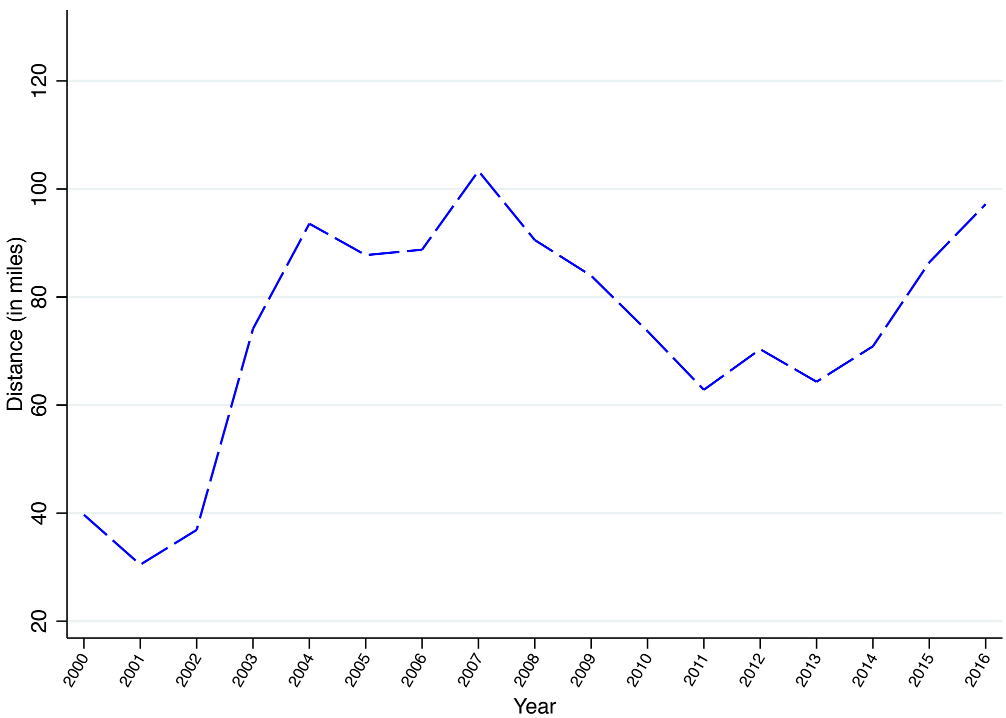


Figure IA.8: Robustness: Alternative Measure of Distance in the Small Business Administration Sample

Figure IA.8 represents the evolution over time of the estimated marginal effect of distance on changes in bank lending measured at different points of the distribution of the HHI coefficient of variation of banks. We compute the marginal effects of distance over time using estimates from the following empirical specification: $\Delta\%SBL_{bct} = \theta_{ct} + \omega_b + \sum_t \gamma_t(Distance \times Year)_{bct} + \sum_t \lambda_t(Distance \times Year \times \sigma HHI_{bct}) + \Gamma X_{bt} + \epsilon_{bct}$, where σHHI_{bct} is the coefficient of variation of the HHI in the branch network of the bank. The marginal effects are computed using the year-specific elasticities of loan volume with respect to distance ($\hat{\gamma}_t$) and the year-specific elasticities of loan volume with respect to distance interacted with σHHI ($\hat{\lambda}_t$). Specifically, we plot $\hat{\gamma}_t + \hat{\lambda}_t \times \sigma HHI$, where $t = 1996, ...2016$, and σHHI takes values $\{\mu - 2\sigma, \mu + 2\sigma\}$, where μ is the mean value of σHHI over the entire sample and σ is the standard deviation of σHHI over the entire sample. The green dashed line is the elasticity of the volume of loans over time for a representative bank-county pair whose value of σHHI is two standard deviations above the mean. The solid red line is the elasticity of the volume of loans over time for a representative bank-county pair whose value of σHHI is two standard deviations below the mean. Data for this figure is computed using the CRA Small Business Lending and the SOD datasets.

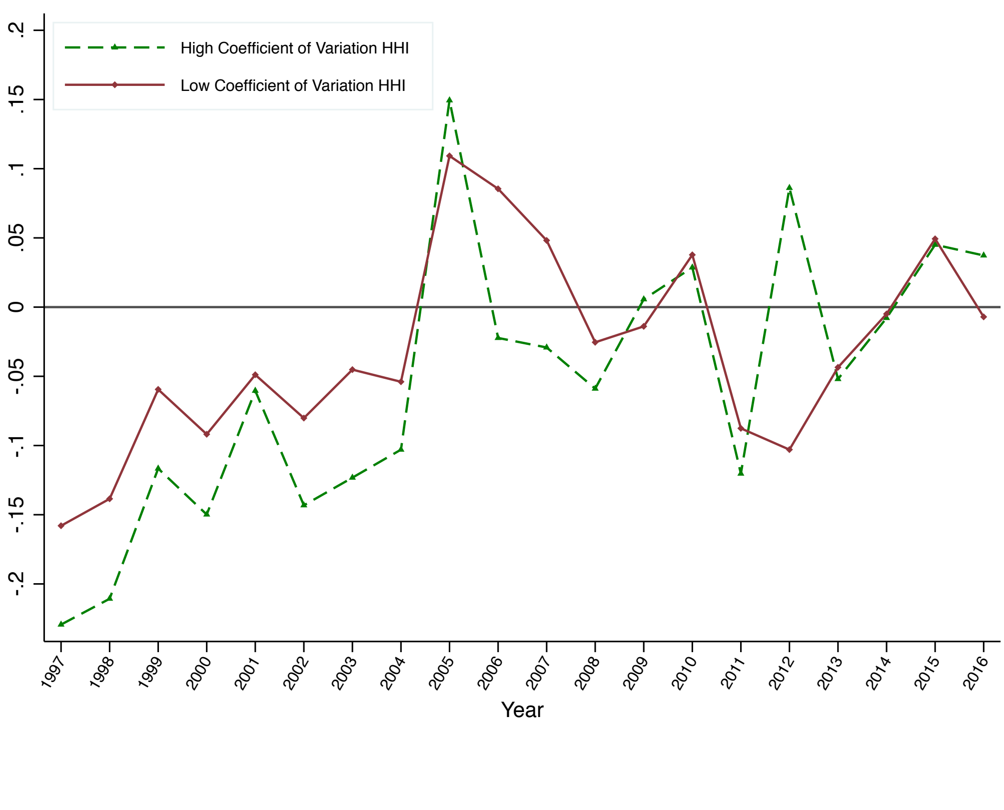


Table IA.1: Alternative Dependent Variables

Table IA.1 reports the coefficients of OLS regressions investigating the effect of distance on alternative measures of small business lending. Δ *Number Loans* is the percent change in the number of loans originated by a bank in a county. *Start* is an indicator variable that takes the value of one if the bank made a loan to a borrower located in a county where the bank had not made loans the previous year. *Exit* is an indicator variable that takes the value of one if the bank stopped lending to a county where the bank had originated a loan during the previous year. Δ *Vol* $\leq$ *100k* is the percent change in the number of loans originated by a bank in a county with principal below \$100,000. *100k* $\leq$ Δ *Vol* $\leq$ *1M* is the percent change in the number of loans originated by a bank in a county with principal amount between \$100,000 and \$1M. *HP-Filtered Real GDP* is the standardize HP-filtered percent change in the real GDP. Real GDP series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Ln(Distance)* is the natural logarithm of the minimum distance between the bank's branch network and the county centroid. All specifications include county-by-year and bank fixed-effects as well as baseline controls for natural logarithm of Total Assets, Share of Commercial & Real Estate Loans, Share of Residential Loans, and Share of Commercial & Industrial Loans. Standard errors are presented in parentheses, and are clustered at the level of the county. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1) Δ Nbr Lns	(2) Start	(3) Exit	(4) Δ Vol $\leq$ 100k	(5) 100k $\leq$ Δ Vol $\leq$ 1M
Ln(Distance)	-0.019***	-0.003***	0.000*	-0.032***	-0.041***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Ln(Distance) $\times$ HP-Filtered Real GDP	0.020***	0.003***	-0.002***	0.031***	0.005***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Observations	5234549	5234549	5234549	5234549	5234549
Adjusted R^2	0.038	0.032	0.027	0.024	0.005
Baseline Controls	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
County-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table IA.2: Alternative Distance Indicators: Out-of-County Dummy

Table IA.2 reports the coefficients of OLS regressions investigating the effect of distance on small business loan originations. The dependent variable are: Δ *Volume Loans* is the percent change in the volume of loans originated by a bank in a county. *HP-Filtered Real GDP* is the standardize HP-filtered percent change in the real GDP. Real GDP series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. Δ *Ln(Unempld Rate* is standardized log difference in the US annual unemployment rate. The unemployment rate series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Spreads* is the standardized net percentage of domestic banks increasing spreads of loan rates over banks' cost of funds to small firms. The series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Out-County Dummy* is an indicator variable that takes the value of one if the borrower is located in a county where the bank does not have a branch presence. The specification includes county-by-year and bank fixed-effects as well as baseline controls for natural logarithm of Total Assets, Share of Commercial & Real Estate Loans, Share of Residential Loans, and Share of Commercial & Industrial Loans. Standard errors are presented in parentheses, and are clustered at the level of the county. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	Δ Volume Loans		
Out-County Dummy	-0.152***	-0.154***	-0.158***
	(0.003)	(0.003)	(0.003)
Out-County Dummy × HP-Filtered Real GDP	0.066***		
	(0.004)		
Out-County Dummy × Δ Ln(Unempld Rate)		-0.034***	
		(0.003)	
Out-County Dummy × Spreads			-0.074***
			(0.003)
Observations	5234549	5234549	5234549
Adjusted R^2	0.016	0.016	0.017
Baseline Controls	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes
County-Year Fixed Effects	Yes	Yes	Yes

Table IA.3: Alternative Distance Indicators: Distance Dummies

Table IA.3 reports the coefficients of OLS regressions investigating the effect of distance on small business loan originations. The dependent variable are: Δ *Volume Loans* is the percent change in the volume of loans originated by a bank in a county. *HP-Filtered Real GDP* is the standardize HP-filtered percent change in the real GDP. Real GDP series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *I(Distance > 25 miles)* is an indicator variable that takes the value of one if the lending distance between borrower and lender exceeds 25 miles. *I(Distance > 50 miles)* is an indicator variable that takes the value of one if the lending distance between borrower and lender exceeds 50 miles. *I(Distance > 100 miles)* is an indicator variable that takes the value of one if the lending distance between borrower and lender exceeds 100 miles. *I(Distance > 250 miles)* is an indicator variable that takes the value of one if the lending distance between borrower and lender exceeds 250 miles. The specification includes county-by-year and bank fixed-effects as well as baseline controls for natural logarithm of Total Assets, Share of Commercial & Real Estate Loans, Share of Residential Loans, and Share of Commercial & Industrial Loans. Standard errors are presented in parentheses, and are clustered at the level of the county. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Δ Volume Loans			
I(Distance>25 miles)	-0.135***			
	(0.002)			
I(Distance>25 miles) × HP-Filtered Real GDP	0.074***			
	(0.003)			
I(Distance>50 miles)		-0.123***		
		(0.002)		
I(Distance>50 miles) × HP-Filtered Real GDP		0.085***		
		(0.002)		
I(Distance>100 miles)			-0.109***	
			(0.002)	
I(Distance>100 miles) × HP-Filtered Real GDP			0.094***	
			(0.002)	
I(Distance>250 miles)				-0.089***
				(0.002)
I(Distance>250 miles) × HP-Filtered Real GDP				0.111***
				(0.002)
Observations	5234549	5234549	5234549	5234549
Adjusted R^2	0.017	0.017	0.017	0.017
Baseline Controls	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
County-Year Fixed Effects	Yes	Yes	Yes	Yes

Table IA.4: Alternative Business Cycle Indicators: State and Local Business Cycle Indicators

Table IA.4 reports the coefficients of OLS regressions investigating the effect of distance on small business loan originations. The dependent variable, Δ *Volume Loans*, is the percent change in the volume of loans originated by a bank in a county. *HP-Filtered Real GDP* is the standardized HP-filtered percent change in the real GDP. Real GDP series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *HP-Filtered State Income p.c.* is the standardized HP-filtered percent change in the state-level personal income *per capita*. The state-level personal income *per capita* series is obtained from the Bureau of Economic Analysis. *HP-Filtered County Income p.c.* is the standardized HP-filtered percent change in the county-level personal income *per capita*. The county-level personal income *per capita* series is obtained from the Bureau of Economic Analysis. *Ln(Distance)* is the natural logarithm of the minimum distance between the bank's branch network and the county centroid. The specification includes county-by-year and bank fixed-effects as well as baseline controls for natural logarithm of Total Assets, Share of Commercial & Real Estate Loans, Share of Residential Loans, and Share of Commercial & Industrial Loans. Standard errors are presented in parentheses, and are clustered at the level of the county. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	Δ Volume Loans				
Ln(Distance)	-0.037***	-0.038***	-0.038***	-0.038***	-0.038***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Distance) × HP-Filtered State Real GDP	0.030***			0.011***	
	(0.001)			(0.001)	
Ln(Distance) × HP-Filtered State Income p.c.		0.017***			-0.006***
		(0.001)			(0.001)
Ln(Distance) × HP-Filtered County Income p.c.			0.004***		-0.003***
			(0.001)		(0.001)
Ln(Distance) × HP-Filtered Real GDP				0.029***	0.040***
				(0.001)	(0.001)
Observations	5217323	5148119	5146638	5217323	5146638
Adjusted R^2	0.017	0.017	0.017	0.018	0.017
Baseline Controls	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
County-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table IA.5: Robustness: Winsorized Dependent Variables

Table IA.5 reports the coefficients of OLS regressions investigating the effect of distance on small business loan originations. The dependent variable, Δ *Volume Loans*, is the Winsorized percent change in the volume of loans originated by a bank in a county. The dependent variable is Winsorized at the top and bottom percentile. *HP-Filtered Real GDP* is the standardized HP-filtered percent change in the real GDP. Real GDP series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Ln(Distance)* is the natural logarithm of the minimum distance between the bank's branch network and the county centroid. The specification includes county-by-year and bank fixed-effects as well as baseline controls for natural logarithm of Total Assets, Share of Commercial & Real Estate Loans, Share of Residential Loans, and Share of Commercial & Industrial Loans. Standard errors are presented in parentheses, and are clustered at the level of the county. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	Δ Volume Loans		
Ln(Distance)	-0.033***	-0.032***	-0.033***
	(0.000)	(0.000)	(0.000)
Ln(Distance) × HP-Filtered Real GDP	0.033***		
	(0.001)		
Ln(Distance) × Δ Ln(Unempld Rate)		-0.018***	
		(0.000)	
Ln(Distance) × Spreads			-0.015***
			(0.000)
Observations	5234549	5234549	5234549
Adjusted R^2	0.017	0.017	0.016
Baseline Controls	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes
County-Year Fixed Effects	Yes	Yes	Yes

Table IA.6: Robustness: Main Results on Subsample of Bank-County Combinations with Minimum Number of Loans

Table IA.6 reports the coefficients of OLS regressions investigating the effect of distance on small business loan originations. The specification reported in each column repeats the main specification in the paper in subsamples of counties-bank combinations totaling a minimum number of loan originations throughout the entire sample period. The dependent variable, Δ *Volume Loans*, is the percent change in the volume of loans originated by a bank in a county. *HP-Filtered Real GDP* is the standardized HP-filtered percent change in the real GDP. Real GDP series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Ln(Distance)* is the natural logarithm of the minimum distance between the bank's branch network and the county centroid. The specification includes county-by-year and bank fixed-effects as well as baseline controls for natural logarithm of Total Assets, Share of Commercial & Real Estate Loans, Share of Residential Loans, and Share of Commercial & Industrial Loans. Standard errors are presented in parentheses, and are clustered at the level of the county. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(3)
	Δ Volume Loans			
Ln(Distance)	-0.018***	-0.010***	-0.000	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Distance) × HP-Filtered Real GDP	0.051***	0.053***	0.055***	0.058***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2298039	1860071	1361031	1029940
Adjusted R^2	0.032	0.038	0.043	0.045
Sample	>10	>20	>50	>100
Baseline Controls	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
County-Year Fixed Effects	Yes	Yes	Yes	Yes

Table IA.7: The Role of Market Concentration (Deposit-Based HHI)

Table IA.7 reports the coefficients of OLS regressions investigating the role that market concentration plays in the relation between lending distance and the credit cycle. The dependent variable Δ *Volume Loans* is the percent change in the volume of loans originated by a bank in a county. *HP-Filtered Real GDP* is the standardized HP-filtered percent change in the real GDP. Real GDP series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. Δ *Ln(Unempld Rate* is standardized log difference in the US annual unemployment rate. The unemployment rate series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Spreads* is the standardized net percentage of domestic banks increasing spreads of loan rates over banks' cost of funds to small firms. The series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Ln(Distance)* is the natural logarithm of the minimum distance between the bank's branch network and the county centroid. *Dep. Mkt. HHI Difference* is the difference between the deposit-market concentration (HHI) in the destination (host) market and origin (home) markets. *Dep. Mkt. HHI Origin* is the deposit-market concentration (HHI) in the origin (home) market. *Dep. Mkt. HHI Destination* is the deposit-market concentration (HHI) in the destination (host) market. Local market concentration is measured as the HHI of the deposit market in each county measured in 1996. The specification includes county-by-year and bank fixed-effects as well as baseline controls for natural logarithm of Total Assets, Share of Commercial & Real Estate Loans, Share of Residential Loans, and Share of Commercial & Industrial Loans. The specification also conditions on the interactions between Dep. Mkt HHI and the business cycle indicators, and Dep. Mkt. HHI and Distance. Standard errors are presented in parentheses, and are clustered at the level of the county. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Δ Volume Loans								
Ln(Distance)	-0.038***	-0.037***	-0.038***	-0.038***	-0.037***	-0.037***	-0.039***	-0.038***	-0.038***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Distance) × HP-Filtered Real GDP	0.036***	0.034***	0.035***						
	(0.001)	(0.001)	(0.001)						
Ln(Distance) × HP-Filtered Real GDP × Dep. Mkt. HHI Destination	0.008***								
	(0.001)								
Ln(Distance) × HP-Filtered Real GDP × Dep. Mkt. HHI Origin		-0.004***							
		(0.001)							
Ln(Distance) × HP-Filtered Real GDP × Dep. Mkt. HHI Difference			0.011***						
			(0.001)						
Ln(Distance) × Δ Ln(Unempld Rate)				-0.018***	-0.016***	-0.017***			
				(0.000)	(0.000)	(0.000)			
Ln(Distance) × Δ Ln(Unempld Rate) × Dep. Mkt. HHI Destination				-0.002***					
				(0.000)					
Ln(Distance) × Δ Ln(Unempld Rate) × Dep. Mkt. HHI Origin					0.007***				
					(0.000)				
Ln(Distance) × Δ Ln(Unempld Rate) × Dep. Mkt. HHI Difference						-0.008***			
						(0.001)			
Ln(Distance) × Spreads							-0.017***	-0.015***	-0.015***
							(0.000)	(0.000)	(0.000)
Ln(Distance) × Spreads × Dep. Mkt. HHI Destination							-0.000		
							(0.000)		
Ln(Distance) × Spreads × Dep. Mkt. HHI Origin								0.003***	
								(0.000)	
Ln(Distance) × Spreads × Dep. Mkt. HHI Difference									-0.002***
									(0.001)
Observations	5216029	5141544	5123471	5216029	5141544	5123471	5216029	5141544	5123471
Adjusted R^2	0.018	0.018	0.018	0.017	0.017	0.017	0.017	0.017	0.017
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.8: The Role of Market Concentration: Out-of-County Dummy

Table IA.8 reports the coefficients of OLS regressions investigating the role that market concentration plays in explaining the heterogeneity in the relation between lending distance and the credit cycle. The dependent variable, Δ *Volume Loans*, is the percent change in the volume of loans originated by a bank in a county. *HP-Filtered Real GDP* is the standardize HP-filtered percent change in the real GDP. Real GDP series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. Δ *Ln(Unempld Rate* is standardized log difference in the US annual unemployment rate. The unemployment rate series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Spreads* is the standardized net percentage of domestic banks increasing spreads of loan rates over banks' cost of funds to small firms. The series is obtained from the Federal Reserve Economic Data (FRED) website of the Federal Reserve of St. Louis. *Out-County Dummy* is an indicator variable that takes the value of one if the lender does not operate a branch in the county of the borrower. *HHI Difference* is the difference in SBL market concentration between destination (host) market and the closest branch (home) market. *HHI Origin* is the SBL market concentration in the closest branch (home) market. *HHI Destination* is the SBL market concentration in the destination (host) market. Local market concentration is measured as the HHI of the small business lending market in each county measured in 1996. The specification includes county-by-year and bank fixed-effects as well as baseline controls for natural logarithm of Total Assets, Share of Commercial & Real Estate Loans, Share of Residential Loans, and Share of Commercial & Industrial Loans. The specification also conditions on the interactions between HHI and the business cycle indicators, and HHI and Distance. Standard errors are presented in parentheses, and are clustered at the level of the county. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Δ Volume Loans				
Out-County Dummy	-0.157***	-0.147***	-0.150***	-0.158***	-0.148***	-0.148***	-0.163***	-0.153***	-0.152***
	(0.003)	(0.003)	(0.009)	(0.003)	(0.003)	(0.007)	(0.003)	(0.003)	(0.007)
Out-County Dummy × HP-Filtered Real GDP	0.069***	0.064***	0.072***						
	(0.004)	(0.004)	(0.009)						
Out-County Dummy × HP-Filtered Real GDP × HHI Destination	0.016**								
	(0.007)								
Out-County Dummy × HP-Filtered Real GDP × HHI Origin		-0.013***							
		(0.003)							
Out-County Dummy × HP-Filtered Real GDP × HHI Difference			0.041						
			(0.033)						
Out-County Dummy × Δ Ln(Unempld Rate)				-0.034***	-0.034***	-0.034***			
				(0.003)	(0.003)	(0.009)			
Out-County Dummy × Δ Ln(Unempld Rate) × HHI Destination				0.001					
				(0.006)					
Out-County Dummy × Δ Ln(Unempld Rate) × HHI Origin					0.013***				
					(0.003)				
Out-County Dummy × Δ Ln(Unempld Rate) × HHI Difference						-0.010			
						(0.032)			
Out-County Dummy × Spreads							-0.075***	-0.072***	-0.071***
							(0.004)	(0.003)	(0.009)
Out-County Dummy × Spreads × HHI Destination							-0.010*		
							(0.006)		
Out-County Dummy × Spreads × HHI Origin								0.005*	
								(0.003)	
Out-County Dummy × Spreads × HHI Difference									-0.001
									(0.030)
Observations	5220264	5132929	5119738	5220264	5132929	5119738	5220264	5132929	5119738
Adjusted R^2	0.016	0.017	0.017	0.016	0.017	0.017	0.016	0.017	0.017
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes