Lending Terms and Industry Dynamics: the Role of Small Banks

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Abstract

The US banking sector has undergone substantial consolidation and increasing concentration over the last few decades. Over the same period, business dynamism of the US economy has declined. This paper studies the link between bank consolidation and the slow-down of US business dynamism. Using loan-level data, I show that banks of different size vary in their pricing patterns. In particular, borrower credit ratings are more strongly associated with loan rates for large bank lenders compared to small bank counterparts. The disparity in price patterns is consistent with different information usage of large and small banks. Small banks rely less on standardized credit measures, making them a more important source of credit for startups compared to large banks. I show that the distribution of banks impact business dynamism by building a general equilibrium model with endogenous occupation and capital structure choice. In such model, a shift in banking sector size distribution can have differential impact on financing conditions of firms with different size, age, and wealth. A quantitative exercise using a calibrated model suggests that bank consolidation may explain up to 80 percent of the total decline in startup rate over the last decade.

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1 Introduction

The US economy has witnessed a decline in business dynamism in its non-financial sector over the last few decades. The share of startups in the total number of firms in the US has almost halved since late 1970s and the decline has remained persistent and widespread across different sectors. Recent studies suggest that this weakening of business dynamism may have a major impact on employment dynamics and aggregate productivity growth (Haltiwanger et al., 2013; Decker et al., 2014). By shifting the age composition of firms and employment share of incumbents, the decline in entry rate can also effect the level and cyclical elasticity of employment (Pugsley and Şahin, 2019).

At the same time, the US banking sector has experienced a substantial consolidation and an increase in market concentration. Commercial banks have become increasingly large and the number of banks has fallen from 8,458 in 2000 to 6,260 in 2016. During this same period, the share of assets held by the five largest banks increased from 28 percent to 47 percent. The decline in the number of banks is largely due to mergers and acquisitions (Corbae and D'erasmo, 2019). More than 90 percent of bank mergers that have taken place since 2000 involved community bank targets and resulted in a large decline in the number of small banks (Jagtiani et al., 2016). This paper explores the link between the increase in banking sector concentration and the decline in startup rate in the non-financial sector, with a focus on the disparity in loan pricing patterns between large and small banks.

One concern with the shift in bank size distribution is its implication for financing conditions of borrowers from small banks, since small and large banks serve different customers. In 2017, the average loan size of large domestic banks was about three times that of small domestic banks. Loans with more than *moderate* risk comprised about a half of total small bank loans while only 20 percent of total large bank loans did (Federal Reserve Statistical Release, 2017).[1] More importantly, small banks have long been recognized as an important source of credit to small and young businesses, largely due to their more flexible lending criteria and higher acceptance rate of small business loan applications (Federal Reserve Bank of New York, 2018). The decrease in the number of small banks may impact the barriers to entry and possibility of survival for these

[1]This refers to the risk category named *Other* in the Survey of Terms of Business Lending survey report. The "Other" category includes loans rated "Acceptable" as well as special mention or classified loans.

businesses.[2]

This paper studies the link between changes in the size distribution of the banking sector and declining business dynamism in the US economy and answers two questions. Does this ongoing trend in bank consolidation contribute to weakening dynamism? To what degree can the bank consolidation explain the change in real sector dynamics over the last decade? I focus on the different information usage and lending criteria of small and large banks to answer these questions. Small banks tend to rely more heavily on less quantifiable information and are more flexible with lending criteria (Berger et al., 2017; Hattori et al., 2015). This gives them an advantage in serving borrowers who find it difficult or costly to prove their ability to repay using standard credit rating measures. These borrowers are often young and small businesses with short credit history and less sound financing conditions. Large banks, on the other hand, are usually required to base their lending decisions on information that is easily quantified and verifiable by a third party.

Given these differences in lending criteria, the shift in banking sector size distribution has two potential implications. First, organizational changes and branch closings may result in a loss of the information advantage held by local banks. Less flexibility and greater dependence on standard credit measures may impose additional costs on young and small businesses, which often face idiosyncratic credit needs. Second, the resulting change in relative cost of borrowing may impact saving decisions of firms. As borrowing becomes more expensive, the value of saving increases. Wealth becomes more important in determining entry and labor input decisions, changing the age-size distribution of businesses. The shift in age-size distribution has an effect on income and wealth distribution as well as employment dynamics of the economy.

The main focus of this paper is to build a model linking banking sector consolidation to non-financial sector dynamics. First, I present new empirical evidence that large and small bank show disparities in loan pricing patterns with respect to hard information (e.g. credit ratings). I use loan-level DealScan data merged with borrower and lender information to show that public

[2]Part of the borrowers affected by the change may replace bank financing with other sources of finance, including private equity and online lenders. The size of private equity market has kept growing since the rapid growth in 1990s. However, the usage of private equity were concentrated in particular industries and size groups (Mckinsey & Company, 2019). With regard to credit information usage, online lenders operate in a much similar way to a large bank than to a small bank. The increased dependence on online lending platform is thus also relevant to this paper which studies the impact of increased dependence on standardized credit information.

credit rating is more strongly associated with loan rates when borrowing from large banks. A fall in credit rating from investment to non-investment grade is associated with on average a 66 basis points larger increase in loan spreads when borrowed from large banks. This result supports the hypothesis that large banks put more weight on hard information in determining lending terms. The pattern is consistent with additional results using loan-level data of small business borrowers from Survey of Consumer Finances data.

To study the quantitative impact of bank consolidation, I then build a general equilibrium model with occupation choice à la Midrigan and Xu (2014) and Buera et al. (2011), adding borrower heterogeneity to the heterogeneous banking sector as in Corbae and D'erasmo (2019). The model includes a banking sector with differently sized banks to study the aggregate implications of bank consolidation. Agents are heterogeneous in their age, credit rating, wealth, and type. Two occupations are available in the economy: firm owner and wage worker. Each firm owner runs a project and faces working capital constraints. The amount of input and the share of working capital to be debt-financed are endogenously determined. The probability of a project succeeding depends on the type of agent and is strictly lower than 1 for all types, generating a positive probability of default. The number of defaults for each agent is recorded in their credit history, which is used by banks to predict the agent's true type.

In the model, the banking sector is composed of banks of two different sizes: *small* banks representing local community banks while *large* banks representing national banks. It is assumed that small banks pay an extra cost per dollar to access deposits but have better technology to screen local borrowers. For each type of borrower, banks participate in a sequential Bertrand competition. Because loan rates change the expected profit and relative cost of self-financing for firm owners, a shift in the size distribution of banks affects the occupation, labor input, and self-financing decisions of agents.

The model is calibrated to match key moments of the US economy in the 2000s to study how the change in banking sector affects firm dynamics of the calibrated economy. I implement the change in the banking sector by increasing the exogenous match rate with large banks to fit the decrease in market share of small banks. I then compare the production choices of agents, including entry, labor input, and financing decisions, and resulting resource distribution of the economy under different distributions of bank types.

I present two main results from the quantitative exercise. First, the model predicts that the increase in banking concentration can explain up to 80 percent of the decline in startup rate over the last decade. The shift in bank distribution increases the cost advantage held by incumbent firms with good credit history. Young firms' loan offers are relatively more sensitive to changes in the banking sector as their credit ratings are less precise. The increase in market share of large banks increases the average weight put on public credit ratings and decreases the average precision of banks' internal screening results. Higher cost incurred from the lower information precision affects old firms only minimally while it further places young firms at a disadvantage. Second, the decline in startup rate and self-employment rate has second-order consequences through increase in income and wealth inequality. A greater gap in borrowing costs among firms crowds out those with high borrowing costs, mostly young firms, and lowers self-employment rate. In addition, the increase in value of wealth for households that sort into entrepreneurship leads to greater wealth inequality.

There is a large literature that uses a model with nontrivial financial sector to study the impact of changes in the credit market, including Gertler and Kiyotaki (2010), Van den Heuvel (2008), and Corbae and D'erasmo (2019). The key new feature of my model relative to the literature is the double heterogeneity in lenders and borrowers. The double-layer of heterogeneity makes it possible to study the impact of a change in bank size distribution on the composition of credit supplied to firms of different characteristics. Model-wise, Corbae and D'erasmo (2019) is closely related in that it builds a banking sector with imperfect competition and persistent heterogeneity. This paper simplifies their banking sector by abstracting from the exit and entry decision of banks but adds borrower heterogeneity using the occupation choice model framework.

Other works have studied the impact of financial frictions on firm dynamics and economic development in a similar heterogeneous agent framework. For instance, Buera et al. (2011) and Midrigan and Xu (2014) use models with endogenous occupation choice to study the effects of financial frictions in the form of collateral constraints. Unlike these works, this paper focuses on the impact of changes in the information usage of banks and resulting lending terms. Cole et al. (2016) presents a model with competitive financial sector that determines the terms of finance using dynamic contracts. This paper uses short-term contracts and instead focuses on the heterogeneity within the banking sector in an imperfect competition setup.

Finally, this paper works as a link between the empirical literature on the disparity in banks' lending practices (Berger et al., 2001; Uchida, 2011) and the recent strand of studies on the declining business dynamism (Hathaway and Litan, 2014; Pugsley and Şahin, 2019). By providing novel evidence of heterogeneous bank lending behaviors and building a model reflecting reported differences, this paper studies the implications of banking sector change on the age and size distribution of firms and proposes the US banking consolidation as a new channel of weakening dynamism.

2 Evidence on Hard Information, Bank Size, and Loan Rates

There is a large volume of literature which studies the difference between small (community) banks and large (national) banks. Small banks tend to serve a narrower range of borrowers in terms of size and region. They are more specialized in the region and industry they serve than large banks (Berger et al., 2017) while the average size of loan is smaller and borrowers are more likely to be small and risky (Federal Reserve Statistical Release, 2017).

In addition to more apparent differences in borrower composition, heterogeneous lending practices of banks has been an important subject of past studies. Small banks differ from large banks in their dependence on *hard* information in the lending process. Hard information refers to the type of information which can be easily standardized, quantified, and transferred to a third party, including the credit score, age, and wealth of borrowers. Large banks tend to depend more heavily on this type of information compared to small banks.[3] According to 2018 FDIC Small Business Lending Survey (Federal Deposit Insurance Corporation, 2018), for example, 64.1 percent of large banks always or almost always evaluate business credit score when evaluating small business borrowers while only 14.8 percent of small banks answered they do. The difference should be most relevant to startup businesses with short credit history and less sound financial background.

In this section, I use loan-level datasets to show how borrower composition differs between

[3] A more traditional approach focuses on how community banks have an advantage at forming relationship with local customers and accumulate not easily transmittable borrower information (Petersen and Rajan, 1994; Berger et al., 2005). Another strand of literature studies the structural difference of banks. Banks with more hierarchical layer may find subjective assessment made by individual loan officer less transmittable to the decision-making layer (Hattori et al., 2015). Berger et al. (2017) shows that large banks are much less specialized than small banks and are more likely to require costly additional financial reports from their borrowers.

small and large banks, even within publicly listed borrower group. Next, I show that loan rates are more strongly associated with public credit ratings when the lender is large. This finding is consistent with large banks' greater dependence on hard information. The same pattern is found in both syndicated loans with publicly listed borrowers and lines of credit provided to small business owners with fewer than 500 employees.

2.1 Data Description and Borrower Composition by Bank Type

I first employ *Dealscan* data consisting of loan-level observations of syndicated loans with detailed loan terms and borrower-lender information. Because syndicated loans involve two or more lenders, only single lead arranger loans are used. This makes it possible to identify the size of the lead arranger bank which played the most active role in assessing the borrower and negotiating terms. The main loan-level variables provided by the data include loan spreads, loan amount, loan maturity, and primary purpose of the loan.

The loan-level information was then merged with Call Reports from the years 2001 to 2012 and *Compustat* data for corresponding borrowing companies. Call Reports include annual total assets of each reporting bank, which was used to construct a dummy variable *Small Bank* which is equal to one if total real asset is less than 10 billion dollars. *Compustat Annual Fundamentals* provides balance sheet data, including initial public offering date, annual net sales of the firm, and Standard & Poor's (S&P) long-term credit ratings for publicly listed firms. To maximize the number of observations, corresponding ratings from Moody's were also included in the data for firms without S&P ratings. Credit ratings obtained were grouped into three grades: investment($\geq$ BBB-), speculative($\geq$ B-, $<$BBB-), and risky($<$B-). This follows standard categories provided by both rating companies.

To merge these data sets, *Dealscan* data was first linked with *Compustat* data using the link provided in Chava and Roberts (2008). Because there is no similar link available between Call Reports and *Dealscan* data, bank names reported in *Dealscan* and Call Reports were used for the initial merge. One problem is that banks do not have the same string denominations across datasets. Therefore, bank names and locations were manually matched and checked to guarantee correct matches. This leaves 5,763 loan-level observations of syndicated loans with publicly listed firms and single bank lead arrangers which have submitted Call Reports. For

Table 1: Summary Statistics

	Large Bank	Small Bank	Total
Loan Size (USD m)	236.6	61.51	226.7
	(560.0)	(293.4)	(549.8)
Loan Spread (basis points)	183.5	282.2	189.1
	(127.3)	(118.8)	(128.9)
Lender Total Assets (USD b)	423.6	3.728	399.8
	(347.0)	(2.420)	(350.7)
Borrower Total Assets (USD b)	4.490	1.112	4.298
	(26.10)	(9.243)	(25.46)
Borrower Age from IPO Date*	10.235	8.336	10.071
	(5.299)	(4.323)	(5.249)
Observations	5436	327	5763

This table provides the mean of key variables from combined dataset of DealScan, Call Reports, and Compustat. Standard deviations are reported in parentheses. Banks with total asset greater than 10 billion dollars are classified as large. *allindrawn* is the difference between the interest rate the borrower pays and the London Interbank Offered Rate in basis points. * Borrower age information is only available for 2,599 large bank borrowers and 244 small bank borrowers from the sample.

Table 2: Credit Ratings Distribution

	Large Bank (%)	Small Bank (%)	Total (%)
Investment	24.15	5.50	23.10
Speculative	29.12	15.90	28.37
Risky	1.80	1.53	1.79
No Rating	44.92	77.06	46.75
Total	100.00	100.00	100.00

Credit ratings are based on *S&P* ratings provided in DealScan data. For firms without the data, comparable ratings from *Moody's* were used if available to construct a combined measure. Firms without ratings information in either *Moody's* or *S&P* ratings were labeled *Unrated* in the data.

the main dependent variable, log of loan rate spread from LIBOR was built using the variable *allindrawn* from *Dealscan*, which is the loan spread from LIBOR rate in basis points.

Table 1 and 2 show how the sample is distributed. The general borrower composition matches that from the aggregate level data. Loans provided by small banks are about a fourth in size on average with higher spreads. The size of borrowers also differs by around 3 billion dollars in total assets on average. While investment grade borrowers constitute about 24 percent of large bank borrowers, the same group composes only 5.5 percent of small bank borrowers. The majority of small bank borrowers remain unrated. Given that the sample only includes publicly listed borrowers, it is not surprising that small bank borrowers make up only about 6 percent of entire observations. For robustness of empirical exercises, I adopt alternative measures of bank size later in this section.

2.2 Loan Pricing Patterns

The goal of this empirical exercise is to study whether loan rates of small and large banks show different correlations with measures of hard information, i.e. credit ratings.[4] The main hypothesis is that large banks are more reliant on hard information when setting loan rates. This should result in large bank loan rates being more strongly correlated with published credit ratings. The baseline specification takes the following form:

$$LoanRate = \beta_1 BankSize + \beta_2 Ratings + \delta BankSize \text{ x } Ratings + \beta_3 \alpha^b + \beta_4 \eta^l + \gamma^t + \epsilon \quad (1)$$

The variable of interest is the interaction term between *Bank Size* variable and credit ratings of borrowers. Each regression also includes borrower level controls (α^b), loan level controls (η^l), and year fixed effects (γ^t). If the hypothesis is correct, worse public credit rating should be associated with a larger increase in loan rates when borrowing from large banks. This implies that the coefficient δ of *Bank Size x Credit Ratings* interaction term should have a negative sign.

Column (1) of Table 3 presents the regression results using equation (1). The *Small Bank* dummy defined above was used as the measure of bank size. On average, large banks offer cheaper loan spreads and loan spreads decrease with better credit ratings. The coefficient on the interaction term between 'Non-investment Grade' and 'Small Bank' is negative and significant. The increase in loan rate associated with worse credit rating is smaller on average if borrowing from small banks. The coefficient implies that the gap in loan rates between non-investment grade and investment grade firms was on average 152 basis points if borrowed from large banks while it was 86 basis points if borrowed from small banks, keeping all other variables at mean values.

A potential concern is that there could be bank characteristics which may be correlated with both loan rates and bank sizes. Then the impact of such characteristics could be captured in

[4]Published credit ratings are usually combinations of financial information of the firm and analytic adjustments made by analysts hired by credit rating agencies. The analytic adjustments should then be approved by internal rating committee of the firm. According to ratings methodology published by S&P ratings, credit ratings reported by private rating agencies mainly comprise of two factors, business risk profile and financial risk profile. Business risk profile includes country specific risk, industry specific risk, and competitive position of the company. Financial risk profile looks at cash flow and leverage of the company. This process mainly involves historical financial statements of the firm with analytic adjustments made by analysts which should be presented to internal rating committee.

Figure 1: Predicted Loan Spread by Credit Ratings, using Different Bank Size Measures

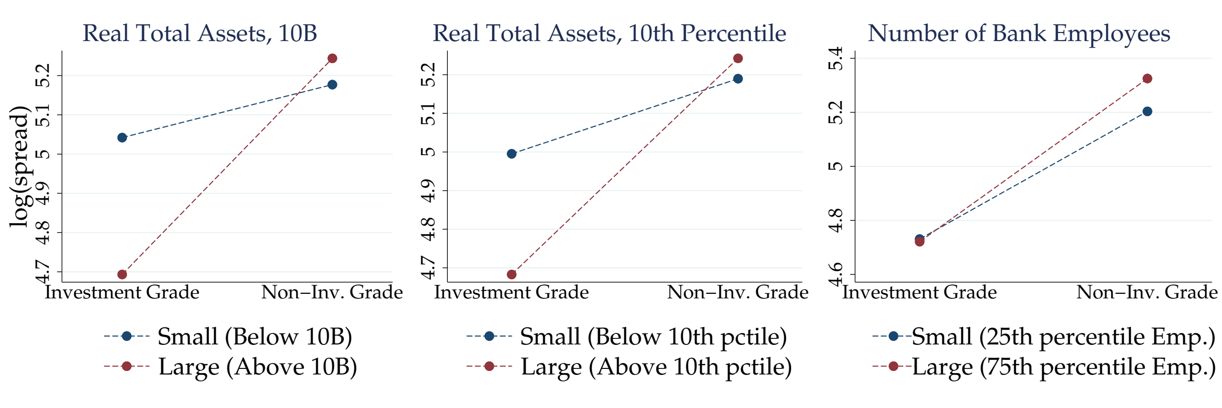


Figure 1 plots predicted loan spread from regression results using equation (1) with different measures of *Small Bank*. For the left panel, *Small Bank* is defined as a bank with real total assets less than 10 Billion US dollars. Borrower controls include the borrower's total assets, debt-to-capital ratio, cash assets, leverage ratio, equity-to-assets ratio, and number of employees. Loan-level controls include the type, purpose, maturity, and secured status of the loan. Borrower industry was defined as the borrower's first digit SIC code. The middle panel uses the 10th percentile in bank total assets as the threshold. The right panel uses the number of bank employees as the continuous measure of bank size and plots the predicted loan spread at 25th percentile and 75th percentile in the number of bank employees. Table 3, A4, and A5 report regression results used for these plots.

our coefficient of interest, δ. To absorb such influence from other bank characteristics, column (3) includes the interaction terms between lagged bank-level controls and borrower credit ratings. The main result remained consistent and significant. Alternative specifications using banks with total assets below the 10th percentile of the asset distribution each year and the number of employees of each bank as measures of bank size are reported in Table A4 and A5. The results remain consistent with the main result.

Figure 1 illustrates the predicted loan rate by credit rating, borrowed from each type of bank. The predicted cost of gap between investment and non-investment grade firms is much larger on average when borrowed from large banks, with all other control variables fixed at mean values.

2.3 Small Business Borrowers

One possible concern is that the data only includes publicly listed firms, which are mostly larger than the ones typically perceived as small businesses. I conduct a supplementary exercise using *Survey of Consumer Finances*, using business owner credit limit as counterpart of credit ratings. The result shows that a similar pattern can be found with smaller businesses loan rates.

While the survey provides only limited data on business loans, it includes data on personal loans with business-related purposes held by business owners. For this robustness check, 696 lines of credit obtained for business-related purposes held by business owners were used. Average credit card limit of each business owner was used as a proxy of the owner's credit score. While the survey does not contain any information about the size of lender, respondents were asked to indicate whether the lender operates in a single state or multiple states. Assuming that banks operating in a single state is smaller on average, I estimate a similar model using the survey data:

$$\begin{aligned} LoanRate = {} & \beta_1 \textit{Single-State} + \beta_2 \textit{Avg. Credit Limit} \\ & + \delta \textit{Single-State} \text{ x } \textit{Avg. Credit Limit} + \beta_3 \alpha^b + \eta^I + \zeta^B + \gamma^t + \epsilon \end{aligned} \tag{2}$$

'Single-State' is a dummy variable which equals to 1 if the respondent indicated that the lender operates in a single state. Each regression also includes business level controls (α^b), industry fixed-effects (η^l), business type fixed-effects (ζ^B) and year fixed effects (γ^t).

Table 4 reports the regression results. Consistent with the previous result with publicly listed firms, the coefficient of the interaction term remains positive and significant. This implies that a lower credit score (proxied by smaller credit limit) is associated with smaller increase in loan rate when borrowing from a single-state lender. Column (2) adds owner's total savings and Column (3) adds owner education and marital status. The results remain robust in both specifications. The finding combined with the main result suggests that the pattern is general across different loan sizes.

2.4 Key takeaways and Discussion

Using loan-level data sets, I show that small and large banks serve different group of borrowers and pricing patterns are in line with the story that they differ in dependence on hard information. Similar patterns are found in loans provided to both large public listed firms and small businesses, suggesting that the structural difference is at least partly playing a role in driving the distinct lending behavior.

One possible concern could be the change in precision of credit ratings over time. If the credit rating technology has improved significantly over time, bank consolidation could have very different implications. Moody's has published its performance of credit ratings over last

100 years. The historical performance report of corporate ratings shows that the accuracy of ratings remained pretty constant since 1970 when they turned to the issuer-pays model.[5] Additionally, it is important to note that the loan performance between large and small banks does not show significant difference. This implies that small banks are not simply taking risky loans and relying on low probability of high returns. Corbae and D'erasmo (2019) reports charge-off and delinquency rates by bank size and actually finds that charge off and delinquency rates are actually statistically higher for Top 10 and top 1% banks. While one needs to keep selection effects in mind, because small banks are much likely to exit the market with high delinquency rate, there is no evidence that small banks have significantly higher charge-off or delinquency rates.

To summarize, small and large banks serve different customer base and display heterogeneous lending practices when dealing with borrower information. Given the difference, the ongoing trend of consolidation in banking industry may have favored firms with already established credit. This may exclude firms which cannot afford costly financial reports because they are not large enough and those without long enough credit history. While large banks can offer more competitive ratings for firms with good standard credit measures, it may be at the cost of younger businesses with potential to grow.

[5] The full report is available at: http://www.moodys.com/viewresearchdoc.aspx?docid=PBC_151096

Table 3: Main Results

	ln(loan spread)		
	(1)	(2)	(3)
Small Bank	0.349***	0.320**	0.283
	(0.131)	(0.153)	(0.207)
Non-investment grade	0.551***	0.556***	1.367**
	(0.0402)	(0.0411)	(0.533)
No rating	0.266***	0.251***	-0.459**
	(0.0432)	(0.0422)	(0.206)
Non-investment grade × Small Bank	-0.416***	-0.377***	-0.398**
	(0.132)	(0.118)	(0.197)
No rating × Small Bank	-0.301**	-0.303**	-0.260
	(0.120)	(0.121)	(0.179)
Constant	5.174***	5.083***	5.296***
	(0.214)	(0.559)	(0.596)
Bank FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5763	5094	5094
R-squared	0.650	0.647	0.649
Borrower Controls	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes
Bank Controls	No	Yes	Yes
Credit Rating × Bank Controls	No	No	Yes

This table reports regression results from equation (1) where the *Small Bank* dummy was used as the measure of bank size. The dependent variable is log of loan spread from LIBOR rate in basis points. *Small Bank* is defined as a bank with total assets less than 10 Billion US dollars. Borrower controls include the borrower's total assets, debt-to-capital ratio, cash assets, leverage ratio, equity-to-assets ratio, and number of employees. Loan-level controls include the type, purpose, maturity, and secured status of the loan. Borrower industry was defined as the borrower's first digit SIC code. Column (2) adds lagged bank-level controls and Column (3) adds interaction terms between lagged bank-level controls and credit ratings. Standard errors are reported in parentheses and clustered at the lender level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Robustness Check: Survey of Consumer Finances

	(1)	(2)	(3)
	Loan rate	Loan rate	Loan rate
Avg. Credit Limit (k)	-3.121***	-3.111***	-4.517**
	(0.602)	(0.599)	(1.852)
Single-State	-55.77*	-57.48*	-231.7***
	(32.46)	(31.83)	(46.44)
Single-State $\times$ Avg. Credit Limit (k)	3.376***	3.142***	3.554***
	(1.039)	(1.033)	(1.024)
ln(Gross Sale)	-5.080	-4.868	-21.47***
	(3.814)	(3.804)	(6.425)
Business Age	0.217	0.200	5.470***
	(0.721)	(0.719)	(1.896)
ln(Annual Income)	-25.74***	-22.21***	70.04***
	(7.673)	(8.024)	(15.61)
Total Savings		-0.0000313**	-0.0000683***
		(0.0000121)	(0.0000241)
Owner Age			-10.53***
			(2.991)
Owner Education			5.644
			(5.301)
Constant	893.1***	854.6***	480.1**
	(75.01)	(78.17)	(215.4)
Industry FE	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	696	696	134
R^2	0.420	0.423	0.710

This table reports regression results from equation (2). All specifications include business industry fixed effects, business type fixed effects, and year fixed effects. The dependent variable is log of loan rate. Column (2) adds total owner savings and Column (3) adds owner's age, education, and marital status. Standard errors are reported in parentheses and clustered at the lender level. *** p<0.01, ** p<0.05, * p<0.1.

3 An Occupation Choice Model with Heterogeneous Lenders and Borrowers

In this section, I construct an occupation choice model with heterogeneous lenders and borrowers. The model economy closely follows that of heterogeneous agent occupation choice model with financial constraints as in Buera et al. (2011) and Midrigan and Xu (2014). By adding nontrivial probability of default and heterogeneous lenders, the model generates variance in cost of funds among agents. As in Corbae and D'erasmo (2019), the lending process involves two types of banks, small (s) and large (L). The model adds borrower heterogeneity to the process and makes it possible to study the impact of changes in the banking sector on credit distribution among borrowers of different type.

Consider an economy composed of N islands where each island represents a state or an industry. The time is discrete. Agents of measure one reside in each island and maximize their utility $U(c) = \log(c)$. Agents are heterogeneous in age (d), public credit rating (η), asset size (a), and type (τ). There are two occupations available: worker and firm owner. As a wage worker, agent earns wage w from providing labor to firm owners. I assume every agent is endowed with one unit of labor. A firm owner of type τ earns income from running a project using labor input, which succeeds with probability $0 < q(\tau) < 1$. It is assumed that $q(\tau)$ increases in τ. A firm owner needs to pay for labor input before profit realizes. The owner makes endogenous capital structure decision by choosing the fraction of working capital to be funded from borrowing.

A finite number of banks operate in each island. I assume that lending decision-makers of small banks have a better knowledge of local firms operating in the island but need to pay extra δ per each dollar of loan. The higher cost of funds can be interpreted as risk premium paid by small banks with less diversified portfolio. This two-dimensional heterogeneity in banking sector leads to difference in average age and firm size served by each type of banks.

3.1 Agents

Agents are heterogeneous in their age d, credit rating η, asset size $a_{min} \leq a \leq a_{max}$, and type τ. Every period, agents choose their occupation between operating a business and working for wage. Age d is the number of consecutive periods each agent has operated as a firm owner and

$0 \leq d \leq \bar{d}$. Each period, every agent's public credit rating is published. The public credit rating equals the true type τ with probability $\psi(d)$. The precision of rating η increases as the firm gets older. $d = 0$ for wage workers. Along with their credit rating, agents also become aware of the loan rate R at which they can borrow from banks. The loan rate differs among agents and depends on public credit rating, age, and banks' internal screening results which will be explained later in this section.

Occupation choices are made based on their probability of success and the cost of operation. The value of an agent with age d, credit rating η, asset size a, and loan rate R, can be expressed as the maximum over the value of becoming a business owner, V_F and the value of becoming a wage worker V_W:

$$V(d, a, \eta, R) = \max\{V_F(d, \eta, a, R), V_W(\eta, a)\} \tag{3}$$

3.1.1 Firm Owners

Firm owners run projects to produce a homogeneous good. Labor l is the only input used for the production. An agent with type τ has access to decreasing returns to scale technology which produces zl^ν with probability $q(\tau)$. l is the labor input choice, $0 < \nu < 1$ is the span of control parameter, and z is the economy-wide aggregate productivity. The wage has to be paid before profit realizes and fraction $0 \leq \gamma \leq 1$ of it can be borrowed from banks. The amount of labor input l and the share of total wage borrowed from banks are chosen endogenously. Once profit realizes, the firm owner either repays the full amount or defaults. It is assumed that banks can perfectly observe the project outcome and keep the collateral in the event of default.[6]

Resource constraints of firm owners depend on project outcomes. Denote savings and consumption choice bundle in the *Success* state as (a'_S, c_S) and those in the *Failure* state as (a'_F, c_F). The Bellman equation of a firm owner with age d, credit rating η, and asset size a

[6]Alternatively, a similar outcome can be achieved by adding incentive compatibility constraint to the maximum loan amount as in Buera et al. (2011). The constraint guarantees that a borrower does not default unless his project fails.

can be then expressed as follows:

$$
\begin{aligned}
V_F(d,a,\eta,R) = \max_{a'_S,\gamma,l} & \mathbb{E}(p_s|d,\eta)\big\{U(c_S)+\beta\max\{\mathbb{E}V_F(d+1,a'_S,\eta',R'),\mathbb{E}V_W(a'_S,\eta')\}\big\}+ \\
& (1-\mathbb{E}(p_s|d,\eta))\big\{U(c_F)+\beta\max\{\mathbb{E}V_F(d+1,a'_F,\eta',R'),\mathbb{E}V_W(a_{min},\eta')\}\big\}
\end{aligned}
\tag{4}
$$

subject to

$$a'_S + c_S = zl^v - wl(\gamma R + (1-\gamma)(1+r)) + (1+r)a \tag{5}$$

$$a'_F + c_F = (1+r)(a-(1-\gamma)wl) \tag{6}$$

$$(1-\gamma)wl \le a \tag{7}$$

$$0 \le \gamma \le 1 \tag{8}$$

$$0 \le a'_S, \;\; 0 \le a'_F \tag{9}$$

where V_W is the value of becoming a worker, p_s is the probability of project success, $1+r$ is the risk free rate, and R is the bank loan rate. The first two constraints are resource constraints. The cost of working capital is the weighted average of loan rate R and risk free rate $1+r$. While self-financing is cheaper than borrowing as long as there is positive default probability, it still accompanies the opportunity cost $1+r$ per dollar. When a firm owner's project succeeds, his income is the sum of profit and return on savings. In the event of default, the firm owner loses the self-financed fraction of the working capital and the collateral held by banks. (7) sets the maximum amount of labor input l so that the amount to be paid in the *Failure* state does not exceed the savings a. Note that the labor input choice l is no longer simply a profit maximization choice as it also appears in the resource constraint of the *Failure* state. The income of the firm owner decreases with the amount of labor input in the event of project failure.

3.1.2 Workers

An agent becomes a worker if the value as a worker is greater than that of running a project. A worker faces the same utility function as a firm owner and chooses consumption c and next period asset holdings a' to maximize lifetime utility. Each worker is endowed with one unit of labor and receives w. The Bellman equation of workers is:

$$V_W(a,\eta) = \max_{c,a'} U(c) + \beta \max\{\mathbb{E}V_F(1,a',\eta',R'), \mathbb{E}V_W(a',\eta')\} \tag{10}$$

subject to

$$a' + c = w + (1+r)a \tag{11}$$

Each period when an agent becomes a worker, the credit history of the agent gets reset. Therefore, the next period age $d' = 1$ for all current workers.

3.2 Banks

A finite number of banks operate in each island. Banks borrow funds from a nonprofit financial intermediary which collects deposits from agents. It is assumed that banks' fund supply is perfectly elastic at set prices so that borrowers do not compete with each other for credit supply. Bankers are assumed to be risk neutral and hand-to-mouth.[7]

There are two types of banks, which are denoted as *small* banks (s) and *large* banks (L). Small and large banks differ in two ways. First, small banks have better technology to process local information. I assume that small banks' internal screening of borrowers is more precise than large banks'. One explanation for the assumption is that there is a stock of *local* or insider information which can only be obtained from close relationship with local residents. Large banks with the need for lending decisions to be verified by a non-local third party may have less incentive to invest in this local information (Nguyen (2019); Jagtiani and Maingi (2019)). Another explanation is that small banks have expertise in the region or industry and have better information compared to banks with diversified service as in Berger et al. (2017). Second, small banks pay extra brokerage fee δ per dollar of funds, which reflects the difference in cost of funds between small and large banks.

The type of loan applicant, τ, determines the probability of project success. While τ is unknown to banks and agents, there are two types of information available in the economy which

[7] This is a simplifying assumption which makes it unnecessary to track each bank's net worth and the amount the bank borrows from depositors.

help banks to assess loan applicants. One is public rating of loan applicants, η, which is published beginning of each period. It is assumed that the precision of public ratings $\psi(d)$, or the probability that the rating is equal to the true type τ, increases with age. In other words, the credit rating is more informative when the agent has operated in the market for a longer period. Each bank additionally conducts internal screening of applicants. Denote the screening result of bank i as ζ_i. The probability of the screening result ζ_i being equal to the true type τ is assumed to be higher for small banks.

Each agent is matched with $m \geq 2$ banks. The probability of being matched with each type of bank is determined exogenously. The probability of being matched with a local bank $0 \leq p \leq 1$ then represents the distribution of local and national bank branches. Once agents are matched with banks, banks participate in a sequential game to win the agent.

3.2.1 Sequential Game between m Banks

The m banks matched with a borrower participate in a sequential game which can be best explained as a sequential Bertrand competition. Banks make loan offers sequentially and the borrower chooses the cheapest offer. The queue of banks is determined randomly from the matching process. I make two assumptions to keep the solution of sequential game tractable.

Assumption 1. Banks maximize their expected payoff per each dollar lent.

Assumption 2. Loan rates are discrete with step size of ϵ.

Assumption 1 makes it possible to analytically solve for banks' expected payoffs. Without the assumption, expected payoffs rely on the system of non-linear equations which determine the optimal labor input decisions of firm owners. Under the assumption, all loan offers are based on zero profit rates of competing banks as long as the profit maximizing rate of the last bank is higher than zero profit rates of its competitors. Assumption 2 is made to ensure the existence of a pure strategy equilibrium. Without the assumption, bank i can always be better off by increasing its original offer by $e < R_i - R_j$ where R_i is bank i's current offer and R_j is the competing bank's offer or the zero profit rate. In practice, ϵ can be as small as desired.

The first bank in the queue, bank b_1 observes the public rating η and conducts internal screening of the agent to receive its private signal ζ_1. Denote the expected payoff of bank b_1 from its loan offer R as $\mathbb{E}\pi(R)$. The bank is aware that it is the first bank in the queue and competing banks will observe its offer. The game can thus be thought of as a signaling game where bank b_1 chooses whether or not to inform other banks of its screening result. Consider the subgame between the first bank in the queue, b_1, and the second bank, b_2. In this setup, there are two possible equilibrium outcomes. A *pooling equilibrium* is the one in which bank b_1 always offers the same loan rate $R_{\text{pool}}(\eta)$ regardless of its internal screening result ζ_1. Bank b_2 receives no new information from the loan rate and the beliefs remain equal to the apriori beliefs based on public rating η and its own screening result.

On the other hand, bank b_1 can choose to differentiate its loan rate offers based on internal screening results and the second possible outcome occurs. Bank b_2 extracts the information from the loan rate, $R_{\text{sep}}(\eta, \zeta_1)$, and updates its beliefs. A *separating equilibrium* is one in which bank b_1 fully reveals its internal screening result with the loan offer. Therefore, bank b_2's posterior belief is that bank b_1's internal screening result $\zeta_1 = z$ for sure where $z \in Z$ where Z is the set of possible screening results. Given that bank b_1 is fully aware that bank b_2 updates its beliefs, the equilibrium condition is that bank b_1's has no incentive to hide its internal screening results. Thus a separating equilibrium exists if the expected payoff from the separating equilibrium is greater than that from the pooling equilibrium:

$$\sum_{\{z\} \in Z} p(\zeta_1 = z|\eta)\mathbb{E}\pi(R_{\text{sep}}(\zeta_1, \eta)) \geq \mathbb{E}\pi(R_{\text{pool}}(\eta)) \tag{12}$$

Once bank b_1 chooses its strategy based on expected payoff per dollar, competing banks in the queue choose their best responses sequentially. Bank b_2 observes bank b_1's offer and updates its beliefs accordingly. Based on its beliefs, bank b_2 also chooses its best action and makes an offer as long as bank b_1's offer is higher than its zero profit rate. The application process continues until the last bank in the queue observes the cheapest previous loan offer R^*, updates its beliefs, and makes choice between offering $R^* - \epsilon$ and giving up the competition.

3.3 Equilibrium

There are N islands, each with identical distribution of banks of each type. Denote public credit rating of agents as η and bank's internal screening result as ζ. Let $n(d, a, \eta, R, \tau)$ be the measure of agents in each state of the invariant distribution and $O(d, a, \eta, R)$ be the occupation choice of agents at each state.

Definition 1. A recursive equilibrium is a set of prices W and r, policy functions for workers , $c^W(a,\eta)$ and $a'^W(a,\eta)$, capital and labor decisions for firm owners, $\gamma(d,a,\eta,R)$ and $l(d,a,\eta,R)$, policy functions for firm owners in *success* state, $c^S(d,a,\eta,R)$ and $a'^S(d,a,\eta,R)$, and in *failure* state, $c^F(d,a,\eta,R)$ and $a'^F(d,a,\eta,R)$, the occupation choice of each agent $O(d,a,\eta,R)$, the invariant distribution of agents in each state $n(d,a,\eta,R,\tau)$, as well as the distribution of banks p and agent type P_g, and banks' and agents' belief of information structure of the economy H, that satisfy

(i) The labor market clears:

$$\int_{d,a,\eta,R,\tau} \mathbb{I}\{V_F(d,a,\eta,R) < V_W(d,a,\eta,R)\} dn_t(d,a,\eta,R,\tau) =$$
$$\int_{d,a,\eta,R,\tau} l(d,a,\eta,R)\mathbb{I}\{V_F(d,a,\eta,R) > V_W(d,a,\eta,R)\} dn_t(d,a,\eta,R,\tau)$$

(ii) The asset market clears:

$$\int_{d,a,\eta,R,\tau} \mathbb{I}\{V_F(d,a,\eta,R) < V_W(d,a,\eta,R)\} a'^W dn_t(d,a,\eta,R,\tau) =$$
$$\int_{d,a,\eta,R,\tau} \mathbb{I}\{V_F(d,a,\eta,R) > V_W(d,a,\eta,R)\}(wl(d,a,\eta,R) - (q(\tau)a'^S(d,a,\eta,R)+$$
$$(1-q(\tau))a'^F(d,a,\eta,R))dn_t(d,a,\eta,R,\tau)$$

(iii) Firm owners optimize decisions under the savings functions $a'^S(d,a,\eta,R)$ and $a'^F(d,a,\eta,R)$, labor input choice $l(d,a,\eta,R)$, and capital structure choice $\gamma(d,a,\eta,R)$
(iv) Workers optimize decisions under the savings function $a'^W(a,\eta)$
(v) The occupation choice $O(d,a,\eta,R)$ is consistent with the value function maximization (3)
(vi) Risk-neutral bankers maximize expected profit per dollar of loan with offers $R(d,a,\eta,\zeta)$ under given rules of the sequential game and consistency of beliefs H

3.3.1 A simple game between 2 banks: an illustration

For illustrative purposes, assume $m = 2$ and the type of bank b_2 is known to bank b_1.[8] The *leader* bank, bank b_1 makes the first offer, knowing that the other bank b_2 will respond to the offer. Bank b_1 faces the risk of winner's curse. It can win the competition only if bank b_2 finds its loan offer not affordable. Therefore, bank b_1 updates its expected default probability accordingly to compute expected profit maximizing loan offer. Denote bank b_i's internal rating result as ζ_i.

Bank b_1's expected payoff depends on the probability of winning the competition, the probability of successful repayment given winning, and the loan spread from its cost of funds. Note that the probability of winning the borrower for bank b_1 remains positive only if bank b_2 (and all other competing banks) finds its offer unaffordable. The relative payoff of separating strategy compared to pooling strategy increases in the borrower default risk and competing banks' precision. If the probability of borrower being a bad type is too high, the pooling strategy becomes too costly for bank b_1 and a separating equilibrium exists.

Similarly, if the competing banks' precision is high enough, information extracted from bank b_1's offer only minimally change bank b_2's beliefs and the relative payoff of pooling strategy is lower than that of separating strategy. Figure 2 illustrates the change in expected payoff of bank b_1 between separating and pooling strategy where $m = 2$ and bank b_1 is a large bank. The payoff from pooling is higher for riskier agents. This is because the expected zero profit rate of bank b_2 increases more sharply with borrower risk without additional information extraction from bank b_1's loan rate.

In a separating equilibrium, bank b_1 calculates the default probability, $1-q(\eta, \zeta_1, z)$, and the zero profit rate of bank b_2, $R_0(\eta, \zeta_1, z)$ given $\zeta_2 = z$. Bank b_1 cannot win unless its offer is lower than $R_0(\eta, \zeta_1, \zeta_2)$. Then the expected payoff per unit of loan from committing to a separating strategy $R(\eta, \zeta_1)$ given $\zeta_2 = z$ can be defined as

$$E\pi(R(\eta,\zeta_1)|\zeta_2 = z) = \mathbb{I}(R(\zeta_1,\eta) < R_0(\eta,\zeta_1,z))\big\{q(\eta,\zeta_1,z)R(\eta,\zeta_1) - r_1\big\}$$

where $q(\eta, \zeta_1, z)$ is the expected probability of success given the credit history η and screening results $(\zeta_1 = z_1, \zeta_2 = z)$.

[8] For quantitative exercises, it is assumed that the type of competitors are unknown to banks earlier in the queue.

Figure 2: Expected Payoff of b_1 using Separating and Pooling Strategy

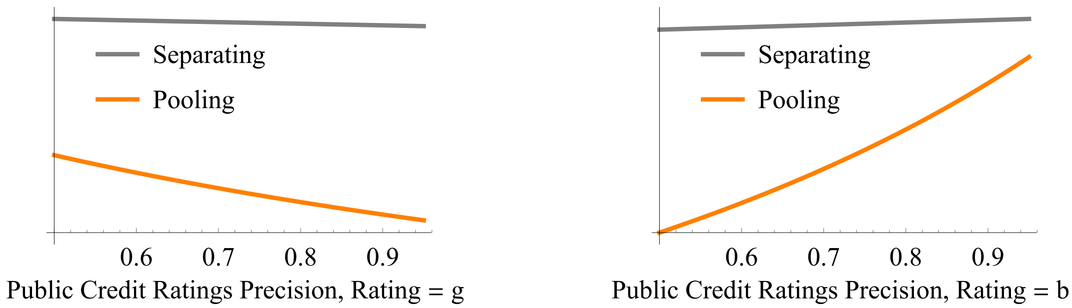


Figure 2 plots the expected payoff from using separating and pooling strategy, given b_1 is a large bank. The left panel assumes that the public credit rating is *good* and the right panel assumes it is *bad*. The internal screening result of b_1 is fixed as *good*.

The expected payoff of b_1 from separating equilibrium is then

$$E\pi_{sep}(\eta) = \sum_{z_1 \in \{g,b\}} P(\zeta_1 = z_1|\eta) \sum_{z_2 \in \{g,b\}} P(\zeta_2 = z_2|\eta, \zeta_1) E\pi(R(\eta, z_1)|\zeta_2 = z_2).$$

The expected payoff function is a step function with thresholds at zero profit rates of bank b_2 given each value of ζ_2. Denote zero profit rates of bank b_2 given $\zeta_2 = z$ as $R_0(\eta, \zeta_1, z)$. Then there are three intervals associated with zero profit rates, $(r, R_0(\eta, \zeta_1, g))$, $(R_0(\eta, \zeta_1, g), R_0(\eta, \zeta_1, b))$, and $(R_0(\eta, \zeta_1, b), \infty)$. Because the payoff function increases with $R(\eta, \zeta_1)$ in each interval, profit maximizing $R(\eta, \zeta_1) \in \{R_0(\eta, \zeta_1, g) - \epsilon, R_0(\eta, \zeta_1, b) - \epsilon\}$ or b_1 makes a zero profit rate offer. Note that bank b_1's offer actually depend on zero profit rate of b_2 given all available information.

On the other hand, the expected payoff per unit of loan from the pooling offer $R(\eta)$ is as follows:

$$E\pi_{pool}(R(\eta)) = \sum_{\{z_1, z_2\} \in Z} P(\zeta_1 = z_1, \zeta_2 = z_2|\eta) \mathbb{I}(R(\eta) < R_0(\eta, z_2)) \{q(\eta, z_1, z_2)R(\eta) - r_1\}$$

Here, the difference is that the probability of winning the competition is now a piecewise function which depends on the zero profit rate of bank b_2 given (η, ζ_2). Bank b_2 can no longer extract information from the offer made by bank b_1. The choice of equilibrium is made based on expected payoff of bank b_1 before any actual internal rating is conducted. Banks commit to the strategy of their choice for each category of loan applicant. After the offer is made, bank b_2 observes the

Figure 3: Loan Rate Offer Distribution, Public Credit Rating $= g$

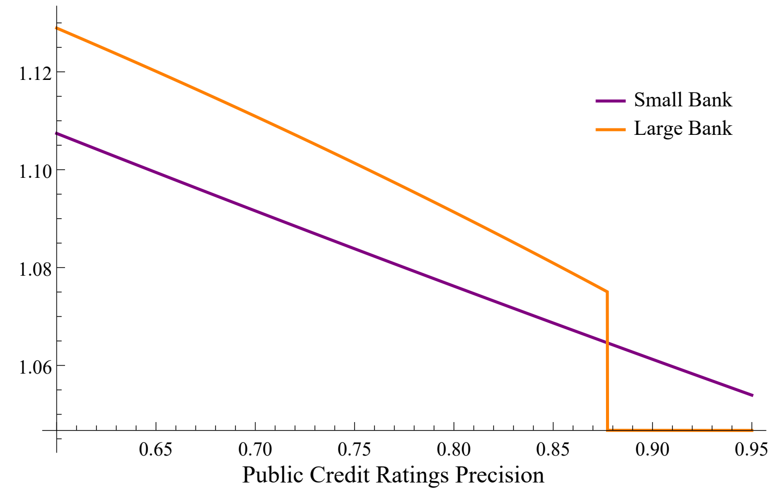


Figure 3 show the distribution of loan rate offer by type of banks, using the simplified setup in 3.2.2. Public credit rating and b_1's internal screening results are assume to be *good*. Other parameter values remain at calibrated values from the further explained in the next section.

offer, R^1, and offers $R^1 - \epsilon$ if it is affordable given available information.

Figure 3 illustrates the loan offer distribution of bank b_1 given public credit ratings precision and assuming separating equilibrium for all borrowers. The kink on the large bank's loan offer curve is the point where the large bank's profit maximizing loan offer transitions from the zero profit rate assuming $\zeta_2 = b$ (bad) to that assuming $\zeta_2 = g$ (good). Offering the zero profit rate assuming $\zeta_2 = g$ increases the probability of winning but entails higher possibility of winner's curse. Large banks choose this strategy only when public credit rating is sufficiently precise, resulting in the crossing of loan offer distribution of these banks with respect to public credit ratings. Note that loan offers of bank b_1 directly determines the final loan rate distribution as bank b_2 either gives up the competition or offers $R^1 - \epsilon$ where R^1 is bank b_1's offer. As a result, the average slope of large bank loan offer scatter with respect to public credit ratings precision is steeper than that of small bank scatter.

3.3.2 Capital Structure and Production Decision

Once occupation choices are made, firm owners make production and capital structure decisions. They endogenously choose the amount of labor input l and the fraction of working capital to be borrowed, γ.

The production input choice problem differs from the standard one period profit maximization problem in that the choice of labor input also determines the resource constraint in the *failure* state. More labor input l implies lower income in the event of default as in (6). Denote the consumption in *success* and *failure* state as c_s and c_f, respectively. Denote the expected probability of succeeding the project given credit history as p_s.

Proposition 1. *At an interior solution, the optimal labor input choice l^* satisfies:*

$$\frac{(1-p_s)U'(c_f)}{p_sU'(c_s)} = \frac{\nu z l^{*\nu-1} - w\{\gamma R + (1-\gamma)(1+r)\}}{w(1+r)(1-\gamma)} \tag{13}$$

and the optimal γ^* satisfies:

$$\frac{(1-p_s)U'(c_f)}{p_sU'(c_s)} = \frac{(R-(1+r))}{(1+r)} \tag{14}$$

Proof. *See Appendix.*

Equations (13) and (14) can be derived directly from rearranging the first order conditions of the utility maximization problem. Equation (13) equates marginal benefit of increasing one unit of labor input in the *success* state to marginal cost in the *failure* state. Similarly, the choice of γ affects both *success* and *failure* state income. Because the borrowing cost R is strictly higher than self-financing cost $1+r$ given positive probability of default, higher γ increases the cost of working capital in the *success* state. On the other hand, high γ limits the cost of default paid in the *failure* state given limited liability assumption as agents only lose self-financed working capital. The numerator of the right-hand side of equation (14) is the marginal cost of increasing γ by one unit in the $success$ state and the denominator is the marginal benefit from income saved in the $failure$ state due to limited liability. That is, the γ^* should be such that agents are indifferent between borrowing and self-financing when $0 < \gamma^* < 1$.

Proposition 2. *In equilibrium, the optimal labor input choice for $\gamma^* > 0$, $l^*_{\gamma>0}$, is equivalent to the one-period profit maximizing labor input choice given the cost wR:*

$$l^*_{\gamma>0} = \left(\frac{wR}{z\nu}\right)^{\frac{1}{\nu-1}} \tag{15}$$

On the other hand, the optimal labor input choice for $\gamma^* = 0$, $l^*_{\gamma=0}$, is always smaller than the *one-period profit maximizing labor input choice.*

$$l^*_{\gamma=0} < \left(\frac{w(1+r)}{\nu z}\right)^{\frac{1}{\nu-1}} \tag{16}$$

Proof. *See Appendix.*

When $\gamma = 1$, the agent is fully borrowing from a bank and does not face any consequences in the event of default. The labor input decision problem thus becomes the standard one period profit maximization problem. Similarly, when $0 < \gamma < 1$, borrowing and self-financing has the same marginal cost at the equilibrium. The labor input choice does not depend on the value of γ and the profit maximizing labor input is equivalent to the value function maximizing labor input where $0 < \gamma < 1$.

The optimal choice of γ mainly depends on agents' cost of borrowing, wealth, and default probability. Borrowing cost R is more expensive than self-financing cost $1 + r$ given there is positive probability of default. Keeping all else equal, γ decreases with the relative cost of borrowing to self-financing, $R - (1 + r)$. At the same time, positive borrowing increases the amount of labor input. Capital constrained agents are likely to borrow more from banks, keeping all else equal. Finally, agents face limited liability in the event of default. That is, only the self-financed share $1-\gamma$ is lost and the income increases in γ in the event of default. The benefit from limited liability is minimal if an agent has default probability close to zero. Therefore, γ increases with default probability with all else fixed.

Figure 4 illustrates the choice of optimal γ given wealth and loan rate. Loan rate R is calculated assuming the same public credit rating (b) and banks' screening results, but with different public credit rating precision given age. The left panel shows the average fraction borrowed from banks with respect to loan rate. The choice of optimal γ is non-monotonic with respect to loan rate because the loan rate also reflects the probability to default. Higher loan rate implies higher default probability as well as more expensive borrowing cost. With higher default probability, the marginal benefit of borrowing from limited liability increases. The non-monotonous relationship persists across different age groups.

The right panel shows the optimal γ with respect to asset. The dependence on borrowing increases as agents become more capital constrained. Note that it is assumed that the public

Figure 4: Capital Structure Decision by Age

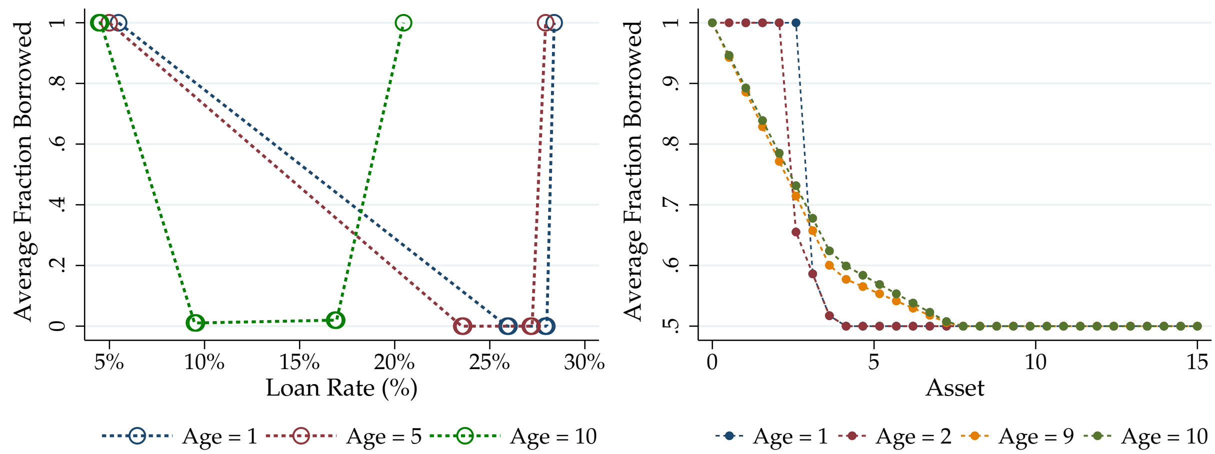


Figure 4 illustrates the optimal capital structure decision of agents by loan rate, asset size, and age. Parameter values are fixed at calibrated values, further illustrated in the next section. In both panels, the agents who become entrepreneurs and with public rating = *good* are only included when calculating the average fraction borrowed from banks.

credit rating is *good* in the plot. Then older agents face cheaper borrowing costs and are more dependent on borrowing in general. At the same time, younger agents are more likely to default than older agents given their credit ratings, explaining the higher dependence of poor younger agents.

4 Quantitative Effects of Bank Consolidation

In this section, I calibrate the benchmark economy to match key annual moments from the US economy between 2001 to 2007. Within the calibrated model, I implement the change in bank distribution by changing the match rate with large banks and quantify the effects on financing and operating decisions of firms and the resulting aggregate moments, including startup rate and top wealth share.

4.1 Calibration

The economy is calibrated to match key moments of the US economy. I assume that there are two discrete types of agents: g (good) and b (bad). There can be two types of banks: s (small) or L (large). I assume the precision of public credit ratings linearly increases with age d.

The following parameters should be specified: the discounting factor β, the span of control parameter ν, the number of loan applications m, the cost of funds difference between small and large banks δ, the probability of success of each type τ, $q(\tau)$, aggregate productivity z, the fraction of good type agents p_g, the rate matched with large banks p, the precision of internal ratings of each type of bank b, $\phi(b)$, and the minimum and maximum precision of public credit ratings ψ_{min} and ψ_{max}.

The span of control parameter ν is set to match the standard value in the literature, $\nu = 0.85$ as in Atkeson and Kehoe (2007). $m = 2$ is set to match the median number of loan applications from the small business credit survey (Federal Reserve Bank of Cleveland, 2013). While the data on the average number of loan applications is limited, it remained mostly constant in available small business survey data. The match rate with large banks p_l is set to match the market share of small banks in total assets. Consistent with the empirical exercise, small banks are defined as banks with real total assets below 10 Billion dollars. δ is set to match the difference in average cost of funding of earning assets between small and larger banks (Federal Deposit Insurance Corporation, 2015).

The remaining parameters are set to match relevant US data in Table 5. β is set to match the risk-free rate $1 + r$ to the annual interest rate during the period, 3.3 percent. The probability of success of each type, $q(\tau)$, determines the nonperforming loan ratio and average loan spread from the risk-free rate $1+r$. With sufficiently high precision of credit ratings, $q(g)$ moves most closely with the default ratio and $q(b)$ mainly determines the average loan rate. Aggregate productivity z relative to endowed total assets and the fraction of good type agents, P_g, together determine the share of entrepreneurs and wealth distribution of the economy. Top wealth share increases with the income gap between entrepreneurs and workers. At the same time, the top wealth share decreases with the share of entrepreneurs in the economy.

Precision parameters, $\phi(s)$, $\phi(L)$, ψ_{min}, and ψ_{max}, collectively determine loan returns of banks, startup rate, and startup employment share. The relative precision of public credit ratings to the precision of banks' internal rating determine the weight put on public credit ratings and the advantage enjoyed by incumbent firms with good credit ratings. The magnitude of the cost advantage enjoyed by old firms combined with the relative cost of borrowing determines the employment distribution. The credit ratings precision of the youngest firms, ψ_{min}, relative to that of oldest firms, ψ_{max}, determines the share of young firms. Finally, the precision of bank

Table 5: Parameterizations

Parameters		Value	Relevant Moments
ν	*Span of control*	0.85	Literature Value
m	*Number of loan applications*	2	Survey Data
δ	*Cost of Funds Difference*	0.037r	Cost Diff. of Funding/Earning Assets
	Matched		
β	*Discounting factor*	0.955	Federal Funds Rate
p	*Match rate with large banks*	0.71	Small bank market share
$q(b), q(g)$	*Probability of success by type*	0.8, 0.985	NPL ratio, average loan spread
z	*Aggregate productivity to max. wealth*	0.33	Top 10 percent wealth share
P_g	*Share of g type*	0.385	Self-employment rate
$\phi(s)$	*Small bank precision*	0.978	Loan returns, small bank
$\phi(L)$	*Large bank precision*	0.9375	Loan returns, large bank
ψ_{min}	*Young firms rating precision*	0.75	Startup rate
ψ_{max}	*Old firms rating precision*	0.985	Startup emp. share

Table 5 reports relevant moments used for parameterizations. For number of loan applications, the median number of loan applications from 2013 Cleveland small business credit survey was used. The rate matched with local banks was set to match the relative frequency of applying to large banks versus small banks from FED small business credit survey. Cost of funds difference was defined as the difference in cost of funds per unit of earning assets between banks with size below 10 billion dollars and with size above that reported in FDIC quarterly banking profile.

screening results determine loan returns of banks. Table 6 reports the data and model generated values of matched moments.

4.2 Bank Size Distribution and Firm Dynamics

To quantify the impact of change in bank size distribution, I conduct a counterfactual exercise in which I vary the value of parameter p, the match rate with large banks. In this analysis, I assume that bank closings or bank mergers involve a loss of information advantage held by small (local) banks. That is, new banks replacing small banks are considered as $large$ banks with noisier local information and cheaper cost of funds.

The exercise relates to recent empirical findings, including those of Berger et al. (2017), Jagtiani and Maingi (2019), and Nguyen (2019). Jagtiani and Maingi (2019) shows that the differential impact of bank mergers on small business lending activities of target and acquiring banks. Following a merger, local small business lending declines significantly more in target bank counties and other banks cannot fully compensate for the decline. Nguyen (2019) shows that the credit supply of regions with higher probability of local branch closings declined following a merger. These results are consistent with the view that bank mergers and consequent closings of local branches are associated with loss of information advantage held by existing borrowers.

Table 6: Matched Moments

Matched Moments	Target Value	Model Generated
Federal funds rate	3.3%	3.30%
NPL ratio	1.6%	1.60%
Top 10% Wealth Share	67.0%	53.10%
Startup Rate	10.2%	7.84%
Startup Emp. Share	2.8%	4.39%
Avg. Spread	4.9%	5.93%
Self-employment rate	11.1%	10.52%
Loan Return, Small Banks	4.4%	3.98%
Loan Return, Large Banks	4.0%	3.89%
Small Bank Market Share	29.5%	28.7%
Unmatched Moments		
loan rate, std (Dealscan data)	0.78	0.82
Debt-to-Output	52.0%	72.0%
Top 10% Income Share	43.0%	28.1%

Table 6 reports calibrated parameter values and relevant moments. For target values of federal funds rate, average spread, and NPL ratio, relevant data series obtained from FRED were used. The income and wealth distribution data uses the updated income and wealth distribution table (Table A1) from Piketty and Saez (2003). Standard deviation of loan spreads is calculated using DealScan data. The startup rate and startup employment share are taken from BDS data. Self-employment rate was calculated using Current Population Survey data, defined as the sum of unincorporated and incorporated self-employed over total employment. Total size ratio between small and large banks and loan returns were calculated using call reports data, where small banks were defined as banks smaller than 10 billion dollars in total assets.

Table 7 summarizes the change in model generated moments computed from the benchmark economy with varying values of p. Target values of small bank market share are 29.5 percent in the benchmark economy and 19.3 percent in 2011-2015. The model predicts a 1.7 percentage point decline in startup rate, which accounts for up to 80 percent of total decline in startup rate over the last ten years. The decline in startup rate accompanies a larger decline in the self-employment, reflecting the crowding out of agents which now face higher cost of borrowing. The decline in self-employment has second-order effects on income and wealth distribution, leading to a greater inequality in the economy.

The change in the loan rate distribution with respect to age drives the main results. Figure 5 shows how the loan rate is distributed across different age groups. The gap in average loan offer between firms with *good* and *bad* ratings increases with age because the precision of public credit ratings increases with age. The accepted loan rate aligns closely with the average loan offers to firms with *good* ratings, suggesting that the variance among accepted loan offers is mostly explained by the difference in banks' internal screening results. With higher precision in public credit ratings, there is lower default risk and less uncertainty associated with old agents' true type. The decline in uncertainty is reflected in the smaller variance in the accepted loan rate.

Table 7: Aggregate Measures

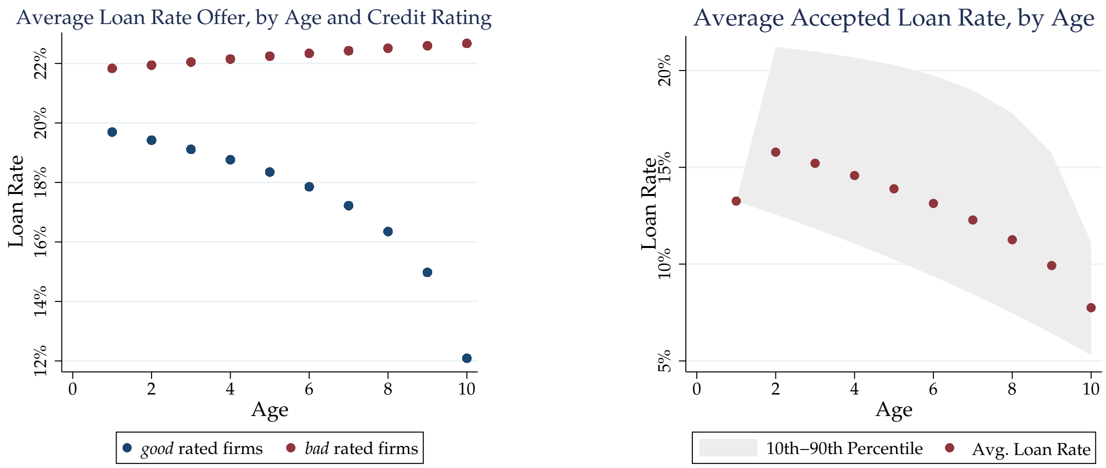
	Model Generated			Data		
	2001-2007	2011-2015	*change*	2001-2007	2011-2015	*change*
Match rate with large banks	0.71	0.80				
Small bank market share (target)	0.287	0.206		0.295	0.193	
Top 10% Wealth	53.1%	59.2%	6.1%	67.00%	72.75%	5.75%
Top 10% Income	26.2%	27.1%	0.9%	43.00%	46.39%	3.39%
Avg. Age	8.341	8.436	0.09	5.220	5.460	0.24
Loan spread, Avg,	5.9%	5.19%	-0.73%	4.92%	2.30%	-2.62%
Startup rate	7.8%	6.11%	-1.73%	10.23%	8.09%	-2.14%
Self-employment rate	10.5%	7.29%	-3.24%	10.98%	10.24%	-0.74%
Self-employment rate (Unincorporated)				7.30%	6.50%	-0.80%
Self-employment rate (Incorporated)				3.62%	3.68%	0.06%

The moments were calculated from steady states given each value of p with other parameters fixed at calibrated values. Share of entrepreneurs is defined as the fraction of agents becoming firm owners. Average spread is defined as the average difference between loan rates and market rate, weighted by loan amount. Share of startups is the share of firms with age $= 1$ in total number of firms.

The variance in loan rate is larger for younger agents, suggesting that the cost of borrowing is much more sensitive to the changes in banking sector precision. Startups' cost of borrowing is most sensitive to the internal screening results and only those with loan rate offers close enough to the lower end become firm owners.

Higher match rate with large banks impacts the loan rate distribution of the economy in two ways. First, more borrowers are matched with large banks which put more weight on public credit ratings. Keeping loan offers from each set of matched banks fixed, this effect alone increases the average weight put on public credit ratings and the extra cost to younger agents incurred from information asymmetry. Second, the higher match rate changes the *leader* bank's expected precision of its competitors' screening results. When determining its optimal loan offer, the leader bank, or the first bank in the queue, of the sequential game takes into account the probability of default given winning. Winning the competition requires its competing bank to find the loan offer unaffordable. Therefore, winning entails greater risk when the competing bank has better knowledge. With higher match rate with large banks, the average precision of competing banks decreases and thereby lowers loan spreads on average. Therefore, the impact from higher p on loan rate depends on the relative size of 1) the sensitivity of loan rate to banks' precision and screening results and 2) the decline in cost incurred from winner's curse. For startups, for example, the impact on loan offers from change in banks' average precision is much larger than the decline in average cost, resulting in the increase in average cost.

Figure 5: Loan Rate Distribution by Age



The left panel of Figure 5 shows the average loan rate offered to agents, by age and credit ratings. Parameter values are fixed at calibrated values. The right panel shows the average and 10th-90th percentile range of accepted loan rate. Accepted loan rate is defined as loan rate at which agents which choose to become firm owners can borrow at. The distribution was estimated using frequency weights calculated from steady state distributions.

The change in match rate and resulting changes in loan rate distribution affect the occupation and labor input choice of agents. In particular, I focus on heterogeneous impact of the change on agents of different age and size. The change in financing costs affects the capital structure decision of firms. With average spread decline with the increase in p, the average dependence on borrowing slightly increases. However, the slight increase is mostly driven by older firms. Figure 6 shows the startups' average fraction of working capital borrowed by asset size. Young firms faced with higher borrowing cost lower the fraction borrowed and rely more heavily on self-financing.

The change in financing costs affects labor input choice and size distribution of firms. The right panel of Figure 7 illustrates the change in average employment by age. Average firm size increases with higher p and resulting cheaper spreads at the aggregate level. However, the increase in size is not evenly distributed across age. The largest impact from the change in p is on the cost of borrowing of small firms. The change in cost of funds is directly reflected in the average employment. While there is minimal impact or a slight increase in employment of older firms, the average employment of young firms falls disproportionately. The strong negative impact on startups' employment decision is consistent with the negative association between bank size measures and annual job gain of startups reported in Figure 8. For the empirical exercise, I use

Figure 6: Average Fraction Borrowed by Startups, by Asset Size

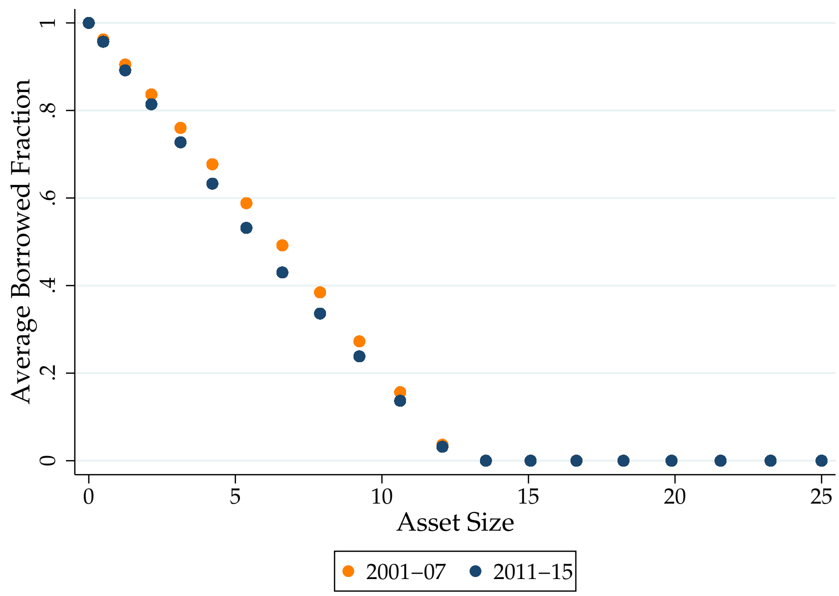


Figure 6 shows the change in average loan rate and employment by age between calibrated economies with $p_l = 0.71$ and $p_l = 0.8$. All other parameters were fixed at calibrated values. The distribution was estimated using frequency weights calculated from steady state distributions.

the state-level gross job gain information for each age group collected from the Census BDS data and run the following regression.

$$\begin{aligned} \mathit{Job\ Gain} = \beta_1 \mathit{Bank\ Size} + \beta_2 \mathit{Firm\ Age} + \delta \mathit{Bank\ Size} \times \mathit{Firm\ Age} + \beta_3 \mathit{State\ GDP} \\ \alpha^s + \zeta^{s \times a} + \gamma^t + \epsilon \end{aligned} \tag{17}$$

Figure 8 shows the marginal effect of different bank size measures ($\beta_1 + \delta$) on annual gross job gain of each firm age group, controlling for state GDP, state fixed effects, year fixed effects, and state-age fixed effects. While the empirical exercise is not intended to provide any evidence for causal relationships, the exercise shows that bank size is negatively and significantly associated with the size of startup employment unlike the association with other age groups.

The shift in age-size distribution of the real sector has nontrivial implications on the aggregate output and distributional margin. The change in match rate results in 10 percent decline in total output of the economy. The decline can mostly explained by the drop in the self-employment rate of the economy. Figure 9 shows the income and wealth distribution change from comparing steady states. The income distribution of the economy is most directly affected by the share of entrepreneurs and relative income of entrepreneurs to market wage received by workers. The self-employment rate of the economy decreases from 10.5 percent to 7.29 percent. Greater variance in borrowing cost crowds out firms with relatively worse financing conditions and those with insufficient wealth. The lower self-employment rate increases the relative income of firm owners to wage workers by crowding out potential employers.

Figure 7: Change in Average Loan Rate and Employment

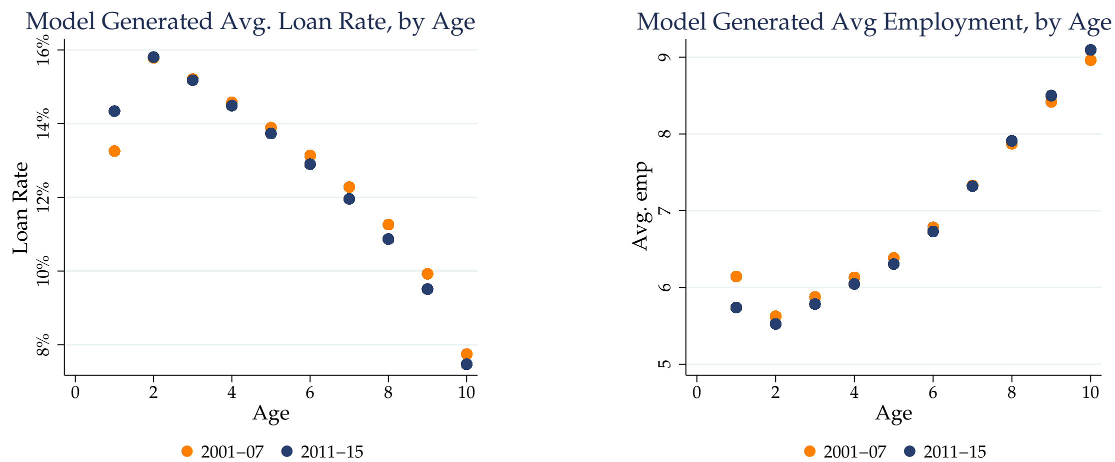


Figure 7 shows the change in average loan rate and employment by age between calibrated economies with $p_l = 0.71$ and $p_l = 0.8$. All other parameters were fixed at calibrated values. The distribution was estimated using frequency weights calculated from steady state distributions.

Figure 8: Marginal Effect on Annual Job Gain from Data, by Age group

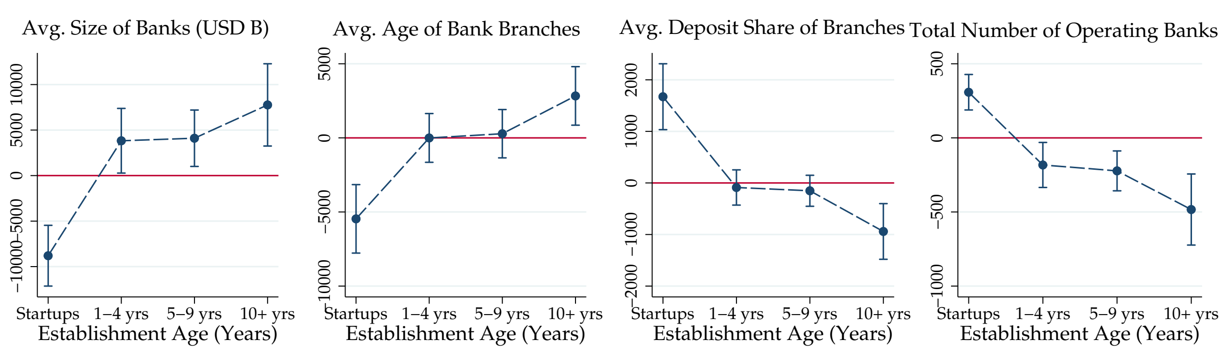


Figure 8 shows the marginal effect of different measures of bank size on annual total job gain by age group and 95% confidence intervals. Bank size measures were computed using Summary of Deposits Data from FDIC. The first panel uses the average total assets of banks in billion USD as bank size measure. The second panel uses the average age of bank branches. The third panel uses the average number of states served by banks operating in the state. The last panel uses the total number of operating banks in the state. State-level annual gross job gains from BDS data was used as the main dependent variable. Standard errors are clustered at State-Age Group-Size Group level. See Table A6 for regression results.

Figure 9: Income and Wealth Distribution Change

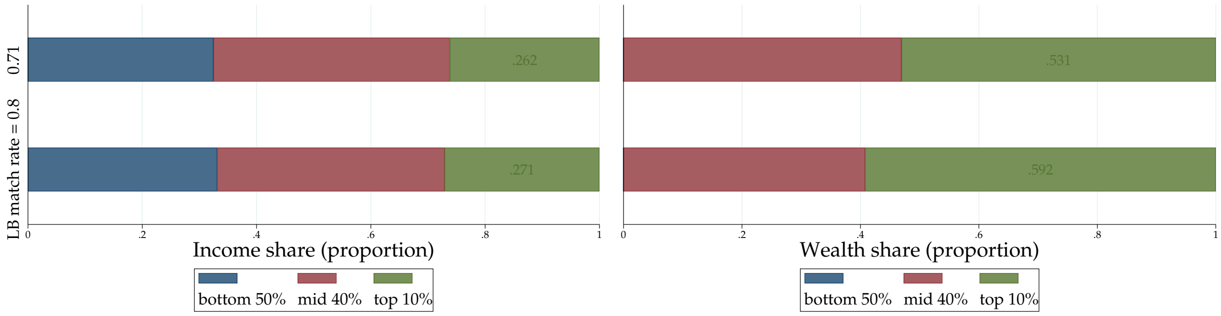


Figure 9 shows the change in income and wealth distribution between calibrated economies with $p_l = 0.71$ and $p_l = 0.8$. All other parameters were fixed at calibrated values. The distribution was estimated using frequency weights calculated from steady state distributions.

4.2.1 The Dodd-Frank Act and Small Community Banks

Quantitative results are also in line with findings from the studies on consequences of stricter bank regulations which followed the financial crisis in 2007-09. The post-crisis changes to bank regulations have increased the regulatory burden imposed on banks. Several studies have explored the impact of the Dodd-Frank Act on the profitability and compliance costs of banks. Despite that the act mainly targeted regulations of *systematically important* banks, the burden on small banks has significantly increased as well. The increase in compliance costs of small banks have resulted in the increased share of small banks contemplating mergers and narrowing of their product lines (Peirce et al., 2014).

Bordo and Duca (2018) documents that the Dodd-Frank Act has resulted in a tightening of credit standards to small firms relative to that of large firms. The study also suggests that the early stages of the act had a large negative effect on business entry. The result is consistent with this paper's finding that lower market share of small banks increases the size of relative cost disadvantage faced by young and small borrowers. Young and small businesses often face idiosyncratic credit needs due to shorter credit history and limited financing options. This paper suggests that the disparities in loan pricing patterns of different sized banks can be a potential channel through which bank regulations may have unintended impact on the real sector dynamics.

5 Conclusion

I study how changes in bank size distribution have differential impact on firms of different age and size. I first use loan-level data with borrower and lender information to study if loan rates offered by large banks display any significant difference from small bank loan rates. I find that large bank loan rates are significantly more strongly associated with published credit ratings of firms, implying that the change in bank size distribution may have differential impact on funding condition of heterogeneous firms. A similar pattern can be found in a supplementary exercise with small businesses. With reported differences of large and small banks in their way of processing standardized and proprietary information, consolidation is likely changing the average way banks set loan terms and amount.

I then build a general equilibrium occupation choice model with discrete types of banks which participate in imperfect competition. Banks differ in their internal ratings precision, which determines the loan rate distribution among heterogeneous agents. Changing the banking sector size distribution of the calibrated economy towards a greater consolidation decreases the startup rate and employment share of young firms and increases the average size of firms in the economy. Through counterfactual exercise, I find that the increase in bank concentration can explain up to 80 percent of total decline in startup rate over the last decade. The increase in bank concentration lowers the average cost of funding which favors older agents with sound credit history and wealthy agents with sufficient collateral. Consequently, bank consolidation subsidizes old, high-credit agents at the cost of opaque young agents with potential to grow further but without prior credit history.

The findings suggest that bank regulations which affect banks' entry, exit, and merger decisions may have unintended consequences through firms' financing conditions. I have abstracted from dynamic decisions of banks which may have led to the change in bank size distribution. Incorporating these dynamic decisions will allow a deeper understanding of these unintended consequences. I also abstract from banks responding to changes in the market and the pool of borrowers. Allowing banks' responses would make it possible to study potential feedback loop between the real and financial sectors.

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A Data Construction

A.1 DealScan Data

The DealScan database contains loan-level information on syndicated loans. This paper uses single-lead arranger loans for which there is only one lead arranger bank recorded in the dataset. This makes it possible to identify the bank which played the main role in information gathering and price setting. 201,694 syndicated loans in the entire sample of 1,858,914 loans are single-lead arranger loans. To complement borrower information, Dealscan data is linked with Compustat data using the link provided in Chava and Roberts (2008). The merged data covers the period from 2001 to 2012 and includes 5,916 observations. Table A1 reports the distribution of observations over the sample period.

I use lender names for the initial match of Dealscan and Call Reports data. For banks with different string denominations across datasets, I manually checked the original name and merger and acquisition history of banks on FDIC BankFind to guarantee correct matches. If a bank was merged into or acquired by another institution after the loan origination, the lender information was matched to the acquired bank's Call Reports data. For cases where there were multiple banks under the same name, the lender information was matched to the bank with closest geographic proximity to the borrower from its headquarter.

Compustat data includes borrower's credit rating provided by Standard and Poor. For the purpose of this paper, I use S&P long term issuer credit rating as borrower's standardized credit measure. The measure was chosen because it is most widely available for sample borrowers. Moody's credit ratings was also matched to borrowers without S&P ratings to complement the limited information and to minimize the selection effect. Table A2 reports the distribution of credit ratings before and after adding Moody's ratings to the sample.

Table A1: Distribution over the Sample Period

Year	Frequency	Percent	Cum. Percent
2001	1,005	16.99	16.99
2002	918	15.52	32.51
2003	743	12.56	45.06
2004	763	12.9	57.96
2005	678	11.46	69.42
2006	491	8.3	77.72
2007	435	7.35	85.07
2008	346	5.85	90.92
2009	178	3.01	93.93
2010	165	2.79	96.72
2011	142	2.4	99.12
2012	52	0.88	100
Total	5,916	100	

This table reports the distribution of DealScan sample merged with Call Reports and Compustat Data over the sample period. Only single-lead arranger loans with both borrower and lender information available are included in the sample.

A.2 Survey of Consumer Finances Data

This paper uses data from the Federal Reserve Board's Survey of Consumer Finances in 2007, 2010, 2013, and 2016. The SCF provides a rich information on financial decisions of small business owners. 95 percent of business owners in the sample ran a business with fewer than 500 employees. An average reported business hired 151 employees, including the owner, family members, and non-paid workers. The data includes information on the type of respondents' primary financial institutions, which can be linked to each loan product reported by respondents.

I use lines of credit reported by business owners with investment-related loan purposes. Investment-related loan purposes include investment in one's own business and investment in assets and real estate. This leaves the sample of 696 observations with main control variables of the regression available. Key variables include loan-level information such as loan amount, interest rate, and maturity and business-level information such as gross sales and age. Table A3 reports summary statistics of the sample.

Table A2: Credit Ratings Distribution

	S&P Credit Ratings		*Moody's Combined*	
	Frequency	Percent	Frequency	Percent
Investment Grade				
AAA	27	0.46	33	0.56
AA+	17	0.29	17	0.29
AA	9	0.15	9	0.15
AA-	62	1.05	68	1.15
A+	87	1.47	87	1.47
A	167	2.82	171	2.89
A-	155	2.62	161	2.72
BBB+	212	3.58	217	3.67
BBB	318	5.38	324	5.48
BBB-	258	4.36	266	4.5
Investment , Total	*1,312*	*22.18*	*1,353*	*22.88*
Non-Investment Grade				
BB+	176	2.97	190	3.21
BB	303	5.12	350	5.92
BB-	317	5.36	390	6.59
B+	305	5.16	372	6.29
B	190	3.21	265	4.48
B-	90	1.52	117	1.98
CCC+	23	0.39	35	0.59
CCC	23	0.39	27	0.46
CCC-	3	0.05	8	0.14
CC	1	0.02	2	0.03
C			2	0.03
D	23	0.39	24	0.41
SD	3	0.05	7	0.12
Non-Investment , Total	*1,457*	*24.63*	*1,789*	*30.25*
Unrated	*3,147*	*53.19*	*2,774*	*46.89*
Total	5,916	100	5,916	100

Credit ratings are based on *S&P* ratings provided in DealScan data. Comparable ratings from *Moody's* were used when available to construct a combined measure. Firms without ratings information in either *Moody's* or *S&P* ratings were labeled *Unrated* in the data.

Table A3: Summary Statistics

Variable	Obs	Mean	Std. Dev.
Line of Credit Rate (basis pts)	1,490	478.98	267.04
Gross Sale (USD m)	1,505	41.24	216.21
Business Age	1,375	14.97	11.43
Owner Annual Income (USD k)	809	378.05	1435.17
Avg. Credit Limit (USD k)	1,442	22.73	17.66

This table provides the mean and standard deviation of key variables from the Survey of Consumer Finances Data. Average credit limit is calculated as the respondent's total credit limit divided by the number of credit cards owned by the respondent.

B Proofs

Proposition 1. *At an interior solution, the optimal labor input choice l^* satisfies:*

$$\frac{(1-p_s)U'(c_f)}{p_sU'(c_s)} = \frac{\nu z l^{*\nu-1} - w\{\gamma R + (1-\gamma)(1+r)\}}{w(1+r)(1-\gamma)}$$

and the optimal γ^* satisfies:

$$\frac{(1-p_s)U'(c_f)}{p_sU'(c_s)} = \frac{(R-(1+r))}{(1+r)}$$

proof. Assume an interior solution. Using first order conditions, I obtain following equations:

$$p_sU'(c_s)\big\{\nu z l^{*\nu-1} - w\{\gamma R + (1-\gamma)(1+r)\}\big\} - (1-p_s)U'(c_f)\{w(1+r)(1-\gamma)\} = 0$$
$$p_sU'(c_s)wl\{R-(1+r)\} - (1-p_s)U'(c_f)wl(1+r) = 0$$

Rearranging the conditions, I obtain the proposition result.

Proposition 2. *In equilibrium, the optimal labor input choice for $\gamma^* > 0$, $l^*_{\gamma>0}$, is equivalent to the one-period profit maximizing labor input choice given the cost wR:*

$$l^*_{\gamma>0} = \left(\frac{wR}{z\nu}\right)^{\frac{1}{\nu-1}}$$

On the other hand, the optimal labor input choice for $\gamma^* = 0$, $l^*_{\gamma=0}$, is always smaller than the one-period profit maximizing labor input choice.

$$l^*_{\gamma=0} < \left(\frac{w(1+r)}{\nu z}\right)^{\frac{1}{\nu-1}}$$

Proof. Assume an interior solution where $0 < \gamma^* < 1$. Then rearranging equations (13) and (14) gives the proposition result (15).

Assuming $\gamma^* = 1$, the first order condition with respect to labor input choice l can be written as:

$$p_sU'(c_s)(\nu z l^{*\nu-1} - wR) = 0 \tag{18}$$

Without self-financing, the income in *failure* state no longer depend on the amount of labor input. The optimal labor input choice problem can then be simplified as a static profit maximization problem.

Assuming $\gamma^* = 0$, on the other hand, I obtain following equation:

$$\frac{(1-p_s)U'(c_f)}{p_s U'(c_s)} = \frac{\nu z l^{*\nu-1} - w(1+r)}{w(1+r)} \tag{19}$$

Then the optimal labor choice can be expressed as:

$$l^*_{\gamma=0} = \left\{ \frac{w(1+r)}{\nu z} \left(\frac{(1-p)U'(c_f)}{pU'(c_s)} + 1 \right) \right\}^{\frac{1}{\nu-1}} < \left(\frac{w(1+r)}{\nu z} \right)^{\frac{1}{\nu-1}} \tag{20}$$

Given any choice of utility function increasing in consumption, the optimal labor choice is lower than the profit maximizing one.

C Supplementary Regression Results

Table A4: Appendix: 10th percentile Measure

	ln(loan spread)		
	(1)	(2)	(3)
Size below 10th pct	0.382***	0.348***	0.317***
	(0.0895)	(0.0938)	(0.112)
Non-investment grade	0.559***	0.563***	1.330**
	(0.0403)	(0.0410)	(0.520)
No rating	0.267***	0.250***	-0.533***
	(0.0429)	(0.0417)	(0.191)
Non-investment grade × Size below 10th pct	-0.459***	-0.406***	-0.406***
	(0.0953)	(0.106)	(0.147)
No rating × Size below 10th pct	-0.254***	-0.197**	-0.158
	(0.0933)	(0.0934)	(0.115)
Constant	5.184***	5.056***	5.320***
	(0.207)	(0.571)	(0.592)
Bank FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5763	5094	5094
R-squared	0.651	0.648	0.650
Borrower Controls	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes
Bank Controls	No	Yes	Yes
Credit Rating × Bank Controls	No	No	Yes

This table reports regression results from equation (1) where the *total assets below 10th percentile* dummy was used as the measure of bank size. The dependent variable is log of loan spread from LIBOR rate in basis points. *Small Bank* is defined as a bank with total assets below 10th percentile each period. Loan-level controls include the type, purpose, maturity, and secured status of the loan. Borrower industry was defined as the firm's first digit SIC code. Column (2) adds lagged bank-level controls and Column (3) adds interaction terms between lagged bank-level controls and credit ratings. Standard errors are reported in parentheses and clustered at the lender level. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Appendix: Employment Measure

	ln(loan spread)		
	(1)	(2)	(3)
ln(Bank Employees)	-0.00453	-0.000826	-0.00825
	(0.0276)	(0.0285)	(0.0300)
Non-investment grade	-0.126	-0.134	0.646**
	(0.239)	(0.230)	(0.299)
No rating	-0.0683	-0.0704	-0.819**
	(0.213)	(0.211)	(0.360)
Non-investment grade $\times$ ln(Bank Employees)	0.0608***	0.0615***	0.0648***
	(0.0230)	(0.0221)	(0.0237)
No rating $\times$ ln(Bank Employees)	0.0281	0.0283	0.0260
	(0.0204)	(0.0201)	(0.0210)
Constant	5.238***	4.961***	5.306***
	(0.422)	(0.780)	(0.837)
Bank FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5090	5090	5090
R-squared	0.648	0.648	0.650
Borrower Controls	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes
Bank Controls	No	Yes	Yes
Credit Rating $\times$ Bank Controls	No	No	Yes

This table reports regression results from equation (1) where the log of number of employees was used as the measure of bank size. The dependent variable is log of loan spread from LIBOR rate in basis points. Loan-level controls include the type, purpose, maturity, and secured status of the loan. Borrower industry was defined as the firm's first digit SIC code. Column (2) adds lagged bank-level controls and Column (3) adds interaction terms between lagged bank-level controls and credit ratings. Standard errors are reported in parentheses and clustered at the lender level. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Appendix: Cross-State Regression

	(1) Job Gains	(2) Job Gains	(3) Job Gains	(4) Job Gains
Avg. Size of Banks (USD B)	-8801.8***			
	(1703.3)			
1-4 yrs × Avg. Size of Banks (USD B)	12629.3***			
	(3411.9)			
5-9 yrs × Avg. Size of Banks (USD B)	12904.5***			
	(3193.5)			
10+ yrs × Avg. Size of Banks (USD B)	16566.6***			
	(3932.5)			
Avg. Age of Bank Branches		-5463.0***		
		(1178.2)		
1-4 yrs × Avg. Age of Bank Branches		5458.4***		
		(1119.1)		
5-9 yrs × Avg. Age of Bank Branches		5744.2***		
		(1111.7)		
10+ yrs × Avg. Age of Bank Branches		8293.5***		
		(1503.9)		
Avg. Deposit Share of Branches			1672.1***	
			(326.0)	
1-4 yrs × Avg. Deposit Share of Branches			-1760.0***	
			(407.7)	
5-9 yrs × Avg. Deposit Share of Branches			-1823.6***	
			(389.6)	
10+ yrs × Avg. Deposit Share of Branches			-2612.9***	
			(538.3)	
Total Number of Operating Banks				308.0***
				(61.05)
1-4 yrs × Total Number of Operating Banks				-490.8***
				(130.5)
5-9 yrs × Total Number of Operating Banks				-530.7***
				(121.9)
10+ yrs × Total Number of Operating Banks				-791.5***
				(177.3)
State GDP Growth	1199.2***	1164.6***	1185.7***	1021.2**
	(426.0)	(426.1)	(425.6)	(389.4)
Year FE	Yes	Yes	Yes	Yes
State × Age FE	Yes	Yes	Yes	Yes
Observations	3672	3672	3672	3672
R^2	0.866	0.860	0.859	0.869

Table A6 reports the regression results from equation 17. Column (1) uses the average total assets of banks in billion USD as bank size measure. Column (2) uses the average age of bank branches. Column (3) uses the average number of states served by banks operating in the state. Column (4) uses the total number of operating banks in the state. State-level annual gross job gains from BDS data was used as the main dependent variable. Standard errors are reported in parentheses and clustered at State-Age Group-Size Group level.