Young Firms' Financing Choices, Investment, and Growth

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Abstract

This paper investigates the impact of access to different financing choices on young firms' future growth paths. According to the Kauffman Firm Survey data, over 2/3 of debt firms rely on credit card borrowing in the first five years of development, not the low-cost bank loans. Because of the selection issues involved in the endogenous financing decisions, I construct a firm life-cycle model with financing constraints. In this model, firms can simultaneously choose up to three debt financing sources: business bank loans, personal bank loans, and credit card borrowing. I find that high-cost credit card borrowing is essential for young firms to overcome financing constraints when they lack access to bank loans. And many firms increase their debt leverage to avoid shrinking their businesses in bad times. In the policy analysis, I exam how young firms react to the increasing financing cost caused by the consolidation process in the local bank industry. When the financing cost is not too high for business bank loan borrowers, firms that solely rely on credit card borrowing will be screened out to become zero-debt firms. Therefore, the fraction of debt firms that have business bank loans increases, and these firms enjoy a high growth trajectory in the long run.

Keywords: Young Firm, Ex-ante heterogeneity, Financing choices, Kauffman firm survey data, firm dynamics

JEL: G32, L25, M13

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1 Introduction

The ability of young firms to obtain financing can have a significant impact on their long-run growth potential. To overcome their borrowing limits, young firms often utilize multiple channels to support their financing demand. According to the survey conducted by the Kauffman Foundation, young firms, such as a newly established restaurant, finance their investments quite differently from older ones. For instance, over half the total debt comes from firm owners' credit card borrowing, but only 1/3 comes from bank loans.

On the other hand, a firm owner with a higher ability not only can organize productivity more efficiently but can also have advantages in seeking financing support, whereas the latter is less well known in the literature of firm dynamics. Understanding the relationship between firms' heterogeneity and access to financing is important for studying the causal effect of financing choices on young firms' growth paths.

Studying such casual effect requires a detailed dataset linking young firms' performance and financing behavior. This research studies this link using the Kauffman Firm Survey dataset (KFS), which span all US non-government sectors and track 4928 newly established firms between 2004 and 2011. The detailed information about firms' economic activities, characteristics, and financing conditions allows me to quantify the effects of heterogeneous young firms' financing choices on their future growth path. From the KFS data, young firms display some distinct features which are neglected in the previous studies. First, nearly half of startups in the sample do not take debt financing at the inception stage. The fraction of non-debt firms in the cohort increases over time. Second, firms that take debt financing primarily rely on three major channels: business bank loans, personal bank loans, and credit card borrowing. Credit card borrowing is the most often used channel among the three channels. Additionally, young firms can utilize multiple channels simultaneously to support their financing demand.

Motivated by the data evidence, I investigate the effect of financing choices on young firms' future growth paths by constructing a firm life-cycle model with financing constraints that allow firms to choose multiple channels simultaneously. Since a firm owner's innate ability can affect the firm's access to the credit, this model also considers the possible influence from the firm owner's characteristics in the financing decisions process. In this paper, firm heterogeneity is dichotomized into low and high types by a set of firm owners' demographic characteristics, including education, work experience, working hours.

In regards to the three major channels previously mentioned, two types of loans offer lower interest rates than credit card borrowing (more than 16% annually), business and personal loans (6%-10% annually). In terms of borrowing limits, business and personal loans are assumed to be backed by the firm's current capital level, among other state variables. When firms become default or bankrupt, lenders of the business loans prioritize claiming the liquidation value, followed by personal loans. In contrast, credit card borrowing is assumed to be free access and has no borrowing limit for firms in this model. Still, young firms have to satisfy the financing feasibility constraints that the future expected liquidation value should cover the new borrowing amount. As firms can borrow from up to three different channels, changes in the mix of channels will affect firms' financing costs.

The cost structure links the interactions between the firm's financing decisions and investment. Changes in the capital and debt adjustment cost will affect the firm's optimal choices over upward or downward adjustment. In my model, firms can accumulate their credit history to access lower costs and safer channels in their later development stages. In other words, getting an advanced financing channel, i.e., the business loan, will increase their probability and borrowing limits to get the business loan in the next period. Since the firm's capital stock affects both the revenue and borrowing limits from bank loans, the optimal debt-taking behavior as well as the investment strategies can vary across the firm capital size distribution[1].

The model estimation procedure is separated into two steps by applying the simulated method in sequence. The task in the first step is to recover the revenue function and borrowing limits for business and personal loans. Then, based on the first step estimation results, I can back out the cost structure for both low and high types in the second step. However, Because estimating borrowing limits requires the knowledge of the firm's optimal choices for new debt borrowing, the model needs to be solved simultaneously.

The estimation results show that taking debt helps firms save the capital adjustment cost. High-type firms have lower adjustment costs than low-type firms. Second, the debt-taking ratio has the U-shape across the firm's capital size distribution, implying that taking debt does not always incentivize firms to grow. The model successfully replicates the downward trend of the debt-taking ratio although the data moments do not target this trend. Using the model to quantitatively evaluate each channel's role in young firms' long-run growth paths, I show that business loans help high-type firms elevate their long-run growth potential. Nevertheless, this effect depends on the free accessibility to credit card borrowing. When the unlimited borrowing assumption is removed, rather than borrowing up to the limits, many young firms will turn to self-financing and no longer take any form of debt.

[1]In the rest of this paper, if not specifically explained, the firm size distribution refers to the firm's capital size distribution.

Based on the estimation results, I further test young firms' reaction to the rising financing cost across funding channels, caused by the increasing concentration in the financial market. The increasingly concentrated local bank industry can result in the rise of the interest rates and growing difficulty in getting low-cost financial products. Small firms that rely on high-cost channels such as credit card suffer the most during this trend. The simulation result indicates that increasing the cost of all channels limits the options for young firms' financing, raises the fraction of non-debt firms in the population,and reduces firms' long-run growth potential. However, in a specific scenario, the increasing financing cost can push firms to reduce the share of borrowing from high-cost channels and better utilize the business loans for growth, resulting in a high growth trajectory.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data and presents empirical facts. The model is described in Sections 4. Section 5 presents the identification strategy and estimation results. The main comparative statistics analysis is shown in Section 6 and 7. Section 8 discusses the impact of the changes in the financing environment. The last Section provides concluding remarks.

2 Literature Review

This research jointly considers how ex-ante heterogeneity and financing constraints impact young firms' dynamics, Three strands of the existing literature are related to this paper. First, it relates to the relationship between firms' ex-ante heterogeneity, firm dynamics, and business cycles, where scholars study how firms' heterogeneity at the entry stage affects the aggregate outcome and growth patterns. Second, this paper's main findings also contribute to the empirical literature of capital structure decisions and firm performance. Third, the young firm's financing decisions are connected to the financing life-cycle literature. Additionally, considering the increasing concentrated local bank industry, this research also provides some policy implications for the impact of the financial market consolidation. Each of these topics is discussed below.

2.1 Firm's ex-ante heterogeneity, future dynamics and business cycles

As more and more evidence shows that firms are different from each other in terms of size and growth rate, economists reach an agreement that firms have different aspirations and can face different constraints. Recent empirical studies on firm dynamics also suggest that startup businesses' entry and exit dynamics play a crucial role in the firm's future growth path and business cycles

(Haltiwanger et al., 2013; Decker et al., 2014). In the data, a large fraction of small businesses exhibits both low growth and low rates of innovation. Haltiwanger et al. (2013) find it is not small businesses that create the most jobs but startups and young, high-growth firms that contribute most to job creation and productivity improvement.

Hurst and Pugsley (2012) make a good survey in analyzing small businesses' heterogeneous behavior. They argue that firms that stay small may not be constrained, but they have little desire to grow big. They emphasize that ignoring the firm's ex-ante heterogeneity can lead to the overstating the influence of firms' ex-post heterogeneity, such as financing frictions. Similarly, Sedláček and Sterk (2017) construct a general equilibrium model and show that startups post entry dynamics can be significantly affected by the economic conditions at the entry stage. In other words, new startups can have different growth potential that directly drives their future growth paths. In their paper, such ex-ante heterogeneity is defined by the differences in the customer base for their products.

Moreover, such heterogeneity can have a long-lasting effect on firms' post-entry dynamics over the business cycle. Moreira (2016) uses micro-level firm data to find that firms born in the downturn start on a smaller scale and remain smaller over their lifestyle. This persistence is related to selection at the entry stage and demand constraints. Using a classic industrial dynamic model (Hopenhayn, 1992; Hopenhayn and Rogerson, 1993), Moreira (2016) finds that more high quality firms enter into the market during economic downturns, grow slowly because of the bad economic status. In contrast, Based on a general equilibrium model with demand constraints, Sedláček and Sterk (2017) show that a positive demand shock relaxes demand constraints during expansions, inducing more high-growth firms to enter the market. High-growth firms expand and grow quickly, driving the growth rate for the cohort. However, during recessions, the share of the high-growth startups is reduced, and low-type firms dominate the cohort.

Besides the composition changes of the different types of firms, Smirnyagin (2019) further adds financial frictions and finds that financial frictions also have non-trivial influences on firms' growth rates. Usually, rapidly growing firms are more vulnerable to financial frictions. To better understand how young firms survive and grow, we need micro-level evidence matching the interactions between firm dynamics and initial conditions, which is the primary goal of this paper.

2.2 Financing constraints and firm performance

In a seminal paper, Evans and Jovanovic (1989) emphasize the importance of financing support for firms, especially during early development periods. Since then, a class of literature has recognized the importance of financing constraints on firm growth and survival. In these studies, credit market frictions are often introduced in the form of collateral constraints that restrict the investment capacity of small firms and play a key role in the transmission of macroeconomic and financial shocks (e.g., Cabral and Mata, 2003; Hennessy and Whited, 2005, 2007; Covas and Den Haan, 2011; Jermann and Quadrini, 2012; Kocherlakota et al., 2000; Quadrini and Cooley, 2001).

In the theoretical literature, young firms' growth rates are correlated with their ability to borrow, and average growth rates decrease as age and size increase. Two papers, Albuquerque and Hopenhayn (2004); Clementi and Hopenhayn (2006), started with information asymmetry to study how borrowing constraints are connected to the firm's performance. Albuquerque and Hopenhayn (2004) study these mechanisms in a model with limited enforceability, while Clementi and Hopenhayn (2006) investigate them under private information. I relax the strict borrowing limits and single borrowing channels that allow variation in financing cost as the borrowing amount increases, which better fits the young businesses' financing situations. Relevant recent contributions by (Khan and Thomas, 2013) feature models of heterogeneous firms in a dynamic stochastic general equilibrium environment. This paper is concentrated on young businesses by modeling constructs a firm life-cycle model by adding the financing constraints, featuring heterogeneity in firms post-entry activities.

In the empirical literature, Cabral and Mata (2003) use a comprehensive micro-level dataset and find that Gibrat's law of the firm size distribution no longer exists when considering young and small businesses. Instead, the model has a good match when considering the financing constraints. From the theoretical predictions, external financing support is crucial to young firms' survival and growth. Hence, young firms, or generally small businesses, should be quite sensitive to financial market fluctuations. However, new empirical evidence shows that financial market fluctuations have insignificant impacts on small business activities.(Greenstone et al., 2020; Crouzet and Mehrotra, 2020) Both papers use a comprehensive firm-level dataset and county-level proxies for the financial shock. Additionally, Carvalho and Grassi (2019) show that large, mature firms drive business cycles. On the other side, during the Great Recession, most young and small business owners suffer from the tightness of the financing constraints. Zarutskie and Yang (2015) confirm that the tighter financing conditions caused by the Great Recession led to the young firms' diminished performance during that period. Regarding the contrasting results in the literature, this paper tries to reconcile the gap between theoretical predictions and empirical evidence.

2.3 Capital structure and financing life cycles

Regarding firms' financing demand, a class of literature lead by Berger and Udell (1998) shows that firms follow certain financing life cycles. Due to informational asymmetry, the business activities and growth potential at the inception stage are quite opaque to outside investors. Often firm owners can only seek funding support from friends or family or expensive credit card borrowing[2]. As the firm survives and grows and accumulates a credit history, the founder can access more financing channels. Following the financing life cycle theory, researchers recognize the importance of financial intermediaries and debt financing to the success of young businesses. Robb and Robinson (2014) find that startups rely heavily on external debt sources. This holds even for those high growth firms that receive angel and venture financing. Different types of firms may have different sensitivity and preferences over certain channels. Cole and Sokolyk (2018) further investigate the effect of business and personal financing channels on firm performance. Understanding the interaction between firm's ex-ante heterogeneity and financing choice is crucial for policy implementations.

To understand firm's financing behavior and capital structure decisions, DeAngelo et al. (2011) construct a dynamic model with endogenous debt borrowing behavior to analyze capital structure dynamics. Strebulaev and Yang (2013) document this interesting heterogeneity across firms and find that zero debt firms are more profitable, pay more taxes, and have higher cash balances than their counterparts. However, we do not know much about whether such features also exist in young businesses.

3 Data and Empirical Analysis

The datasets for this research come from two sources. The young firm's micro-level data comes from the Kauffman Firm Survey (KFS) data, which provides information on young firms' growth and financing portfolios. The second source comes from the summary of deposit from the FDIC website and Community Reinvestment Act (CRA) disclosure data from the Federal Financial Institutions Examination Council (FFIEC).

[2]However, a few firms with long time growth potential can attract Angel investors or venture capitalists. Moreover, these firms are mainly concentrated in the high-tech industries with breakthrough technologies. Such differences across firms provide another piece of evidence for the ex-ante heterogeneity. But this paper focuses on debt financing channels.

3.1 Kauffman Firm Survey data

The KFS is a longitudinal survey of US businesses that began their operations in 2004 and included both employer and non-employer firms in its base sample. To provide a representative sample of new businesses, KFS used the businesses listed in the Dun and Bradstreet (D&B) database in 2004 as the sampling source. The KFS surveyed 4,928 sample firms from 32,469 businesses in the D&B database[3]. Compared with other data sets, the KFS is the panel data set of young firms that includes information on firm-level financial and economic outcomes, innovation activities, and owners' demographic features. The detailed record of the firm's financing sources and firm characteristics allows us to link the ex-ante firm characteristics, financing choice, and firms' growth dynamics. Throughout this research, I use the whole sample for empirical analysis[4].

3.2 The supply of financing

To study the interplay between firm dynamics and the financing market, we also need to consider the variations in the local financing environment. The demographic information includes the county-level household income, population, and population density from the census data. The institutional and branch information of the banks can be obtained from the summary of deposit report of the FDIC website.

Young firms' financing choices also depend on the local financing supply-side variation. I borrow the local credit supply shocks from Greenstone et al. (2020). This proxy is constructed using Community Reinvestment Act (CRA) disclosure data from the Federal Financial Institutions Examination Council (FFIEC). I follow the same procedure to create the control proxy that approximates the credit shocks. Because firms in the KFS dataset started in 2004, I use the credit shocks in 2004 as the initial credit shock in the rest of the empirical analysis.

[3] See https://www.kauffman.org/what-we-do/research/kauffman-firm-survey-series for the overview of KFS reports in different years. The detailed data dictionary, as well as downloadable questionnaires, can be achieved through SSRN https://papers.ssrn.com/. See also Farhat and Robb (2014) for more detail on the KFS questionnaire and survey design. Zarutskie and Yang (2015) have a good summary of the pros and cons of KFS dataset.

[4] But due to the missing data and unexpected exit, there is a different in the sample size for longitudinal (3140) and cross sectional analysis (4928). Except for the standard errors, applying different sample size does not affect the main results.

3.3 Young firms' financing choices

The existing research on firm dynamics or corporate finance is mainly concentrated on large, mature firms. However, young firms' financing choices, based on the KFS dataset, have some distinct features.

Nearly half of young firms have zero debt and the ratio increases over time A class of literature has shown that financial constraints are a significant determinant of firms' investment decisions, particularly for young firms (Evans and Jovanovic, 1989). If the constraints are relaxed in future periods, those constrained firms will grow to the optimal size. According to the theory, as firms survive and accumulate a good credit record over time, we should expect that they will get access to funding support. However, young firms in the KFS data display a downward trend of debt-taking behavior: young firms seem to reduce their reliance on external financing sources over time. From the figure 1, we see the fraction of firms with debt declines from around 50% at the beginning to near 40% at the end of the sampling period. As a comparison, (Strebulaev and Yang, 2013) calculate that from 1962 to 2009, an average 10.2% of large public non-financial US firms have zero debt. Zero-leverage behavior seems more prevalent in the young and small businesses' operation strategies.

When comparing debt firms with non-debt firms from figure 2, we see non-debt firms have a smaller firm size (measured by employment) and less revenue return over assets. However, the net profit for non-debt firms outperforms their counterparts. Compared with the leveraged young firms, non-debt firms have higher profit returns but do not want to grow big, as shown in figure 3 and 4. The debt-taking behavior of young firms from the data shows that firms with debt will quickly turn to self-financing and stay small after a few years of development.

Young firms with debt rely heavily on bank financing Now we turn to the firms that have positive debt. According to the financing life-cycle theory, startups find difficulty seeking funding sources due to frictions in capital markets. Instead, they use informal channels such as borrowing from family, friends, or wealthy persons. Then, as the firm survives and accumulates a good credit record, they can turn to outside financing like bank loans (Stiglitz and Weiss, 1981; Berger and Udell, 1998; Sahlman, 1990). Based on the theory's prediction, the intermediated external finance options, such as bank financing, are hard for firms in their early development periods. However, from the data, we see that even at the beginning, young firms rely heavily on external financing, especially from debt financing. The three major bank borrowing channels are business loans, personal loans, and credit card borrowing.

Within the three channels, credit card borrowing contribute to more than 60%, shown in figure 5. On the contrary, business bank loans, which we used to believe the most important credit channel for young and small businesses, only contribute less than 20% among the three major channels. Figure 5 also indicates that business bank loans and personal bank loans have quite a strong substitution pattern over time. The reliance on credit card borrowing is also increasing, partly because most small firms use credit card borrowing to finance their operational capital.

Young firms utilize multiple financing channels to support their investment Figure 6 shows that to overcome the financial constraints, one-third of young firms take multiple funding channels instead of solely relying on one channel. Moreover, firms that take multiple channels usually borrow a lot compared with one-channel firms. The exception is the firms with business bank loans with a bigger size and better business running status. Additionally, because of the downward trend of debt-taking behavior for young firms, given that the ratio for the number of channels that firms take is relatively stable over time, more and more firms tend to use multiple channels to compensate for their financing demand as they ages.

3.4 The growth pattern of young firms

Among these young firms, the demographic characteristics of the firm owners show a level of heterogeneity. Table 1 and 2 presents the descriptive statistics on firm and primary owner characteristics. Regarding the firm owner's demographics, the primary owner, on average, is 45 years old when starting their businesses. They often stay in the same industry with their previous experience, 13 years on average. For educational background, two out of three primary owners have some college education or hold a college (bachelor's) degree, and one in five holds a graduate degree. Over the sample period, around 6% of firms come from the high-tech companies[5], 19% own at least one intellectual property[6].The firm's credit risk[7] reflects the firm's accessibility to external financing sources. The data shows that a major fraction of firms do not have a high credit record at the

[5] The KFS defi nes high- tech industries as those with two- digit SIC codes: 28 chemicals and allied products, 35 industrial machinery and equipment, 36 electrical and electronic equipment, and 38 instruments and related products. For more information, please check the https://www.kauffman.org/what-we-do/entrepreneurship/research/kauffman-firm-survey and Zarutskie and Yang (2015).

[6] The intellectual property includes patent, trademark, and copyright

[7] Based on their businesses' credit risks, firms are divided into 5 categories, where 1 indicates high credit score and lowest risk. Correspondingly, 5 indicates low credit score and highest risk.

beginning. As young firms survive and accumulate business credit records, the average credit scores increase.

In the data, there are a large group of firms (60%) with zero employees at inception stage. Even at the end of the sampling period (2011), 52% of the survival firms were still without any employees. Moreover, firms with more than 19 employees (excluding the primary owner) only occupied 4% of the total population from the sample in 2011. For many small businesses, hiring people involves nontrivial adjustment for payroll, tax format, and even the firm's legal status. without a considerable significant profit and promising business activities, most self-employed firm owners are unlikely to hire employees.

Contrary to the insignificant employment growth, firms actively adjust the capital/assets in their early development periods. figure 7 show the average capital adjustment ratio of young firms over time. From figure 7, we see firms not only increase their assets in each period, but the downward adjustment is also very active over time. The frequent capital adjustment and the infrequent employment variation indicate that young firms tend to adjust capital instead of labor for the market shock.

In recent literature, there is a growing attention to studying the firms' conditions at the entry stage. To study the relationship among young firms' growth pattern, financing choices, and their ex-ante characteristics, I classify the sample into low and high types using the clustering method. Appendix A contains the details concerning the classification procedure. With the help of this procedure, firms in the data are divided into high and low two sub-groups. Regarding the classification, High-type firms have higher education levels, more senior working experience, and longer working hours. This ex-ante heterogeneity affects the firms' future growth and financing decisions. The future economic activities and financing statistics are shown in table 3 and 4.

From the two tables, we see that high-type firms, on average, have higher growth rates and better chances of getting business bank loans than low-type firms. More specifically, the firm's size and revenue return increase over time for both types, but high-type firms have larger sizes and better revenue returns. Compared with high-type firms, low-type firms are harder to access credit, especially for business loans. In the rest of the analysis, young firms' heterogeneity is represented by low and high types.

3.5 Firm performance and financing choices

Seeing these features on young firms' financing choices, I want to know how the choices of financing channels are connected to the firms' future development. The choices of different financing channels can also be affected by the financing-supply side variation. To control for the supply-side influence, I borrow the "credit supply shock" from Greenstone et al. (2020) into the analysis. The formal econometric specifications are specified as follows:

$$y_{i,g,T} = \beta \mathrm{Fin}_{i,0} + \delta D_{g,0} + \gamma_1 X_{i,0} + \gamma_2 G_{g,0} + \varepsilon_{i,T},$$

where i represent the individual firm, g represents the local geographic specification, 0 represent the initial period, and T represents the period T's firm development status ($T = 1, 2, 3$). On the right hand side, $\mathrm{Fin}_{i,0}$ denotes the major financing channels that firm i uses, including business bank loan, personal bank loans, and credit card borrowing. $D_{g,0}$ denotes the initial period credit supply shock[8]; vector$X_{i,0}$ represents firm level characteristics; and $G_{i,0}$ denotes local financing environment (at MSA level) for firm i in initial period, which includes the local bank concentration index, the number of branches, and the deposit amount for the local market; and $\varepsilon_{i,T}$ denotes residuals. On the left-hand side, $y_{i,g,T}$ denotes firm i's accumulated asset/employment growth rate at period T.

The report is summarized in table 5, 6 and 7, representing the regression results of asset, employment and revenue growth rate, respectively, on firm's initial financing choices. From the table 5, we see firm's assets growth is significantly correlated with the accessibility to business bank loans. But the assets accumulation does not respond to the external credit supply shocks after controlling the local demographic and financing environment. On the contrary, taking business bank loans does not have a positive influence on firm's employment growth, as shown in table 6. On the other side, personal bank loan helps young firms grow bigger in their early development periods.

Credit card borrowing is negatively correlated with employment growth after three years of development. Regarding the high risk of credit card borrowing, the negative correlation explains the connection between small firms and their reliance on credit card borrowing. Nevertheless, the negative impact of business bank loans on firms' employment variation may imply that labor adjustment for young firms is more difficult than asset adjustment. When we turn to the table 7, the revenue growth rate, we see that credit card borrowing in the first and second years of development has a positive and significant impact. But after three years of development, we see firms with business bank loans have higher revenue growth. The regression results show that different funding

[8] The construction of the credit supply shock follows the same setup as (Greenstone et al., 2020).

channels' choices can impact firms' future dynamic patterns in different directions. However, the interactions of firm financing choices and their investment decisions can not be observed directly from the reduced form analysis, which requires a structure model for further investigation.

4 A Stylized Firm Life Cycle Model

In this research, I construct a simple firm life cycle model to study the relationship between young firms' long-run growth pattern, measured by capital accumulation, and their financing choices. The main distinction in this model is that young firms can choose up to three different debt financing channels in each period[9]. This relaxation helps young firms bypass the financing constraint caused by a single channel in the previous literature. Based on empirical evidence, the three main channels discussed in the model are business bank loans, personal bank loans, and credit card borrowing. Besides firms' financing decisions, this model also considers the heterogeneity among young firms. For example, by running the same restaurant, an experienced chief naturally works better than someone who has no previous experience working in the restaurant. Including the ex-ante heterogeneity helps identify the causal effects of financing decisions on young firms' dynamics.

4.1 Timeline

Figure 8 depicts the general timeline of young firms' dynamics and their decisions graphically. This model is about the firm's life cycle of one cohort. Time is discrete and denoted by t. At the initial stage ($t = 0$), each startup is endowed with a certain amount of capital to start their business. Regarding the heterogeneity, based on the firm owner's ability, each firm belongs to either low or high-type, represented by A_i. In the middle of the period, firms seek external financing support and learn how much they can borrow in each channel based on the received financing signals. At the end of the period, firms pay adjustment costs and make final investment and borrowing decisions.

At the beginning of the next period, firms learn the market shock and receive the realized revenue. After paying off the operational and interest cost, firms decide whether to continue the production or exit. When a firm decides to leave the market, the firm will start the liquidation process: selling off the capital, paying off the outstanding debt, and collecting the remaining value. If a firm

[9]Indeed, some small businesses that have long-term growth potential are favored by PE/VC firms. But these firms are only a 4% of the total sample, and half of them are missing during the later survey periods. Since this research is about debt financing decisions, equity financing activities are not the focus for the time being.

cannot cover the debt payment, the firm will immediately become bankrupt and start the liquidation process. On the other side, if a firm earns enough revenue and decides to continue running the business, the firm will search for financing support and make investment and borrowing decisions again. In the rest of periods, the firm will repeat all the above actions. The detailed decision process will be discussed in the following subsections.

4.2 Environment

Because the model is concentrated on young firms, this paper assumes that firms are price takers and production goods are homogeneous. Moreover, this model is about a firm's life cycle so that there is no discussion of new entrants. Time is discrete, denoted by t. Young firms' heterogeneity stems from firm owners' demographic characteristics. Based on the classification procedure in the previous section, firms can be either low or high type, denoted by $A \in \{A^L, A^H\}$, which affects revenue and financing decisions. Young firms in this model accumulate capital, denoted by k, for production and revenue earning. For notational abbreviation, I drop the index of firm i in the rest of the model description.

4.3 Production technology

To match the data while keeping the representation of young firms' behavior, I choose a revenue-based production technology:

$$\pi_t = roa(k_t, A, \lambda_t, z_t) \tag{1}$$

where k_t is the capital stock, A is the firm's type, and λ_t is the firm's credit rating record, which will be discussed in the firm's financing decision part. z_t summarizes the market shocks and follows an idiosyncratic $i.i.d$ distribution, denoted by F_z. The law of motion for capital accumulation is given by

$$k_{t+1} = \begin{cases} (1-\delta)k_t + i_t & \text{if } i_t \geq 0 \\ (1-\delta)k_t + \frac{1}{\kappa}i_t & \text{if } i_t < 0 \end{cases} \tag{2}$$

where i_t represents the investments, and δ denotes the capital depreciation rate. In this model, investment is allowed to be negative, which means firm owners can downward adjust their capital stock during the bad business periods. Selling off the installed capital incurs a disassembly cost (can be due to the transaction costs or lemon market), denoted by κ. Moreover, the model assumes that capital investment entails convex adjustment cost,

$$C_t^k = c_{k1}^{-} k_{it} 1_{\{k_{it+1} < k_t\}} + c_{k1}^{+} k_{it} 1_{\{k_{it+1} \geq k_t\}} + \frac{c_{k2}}{2} \left(\frac{i_t}{k_t} \right)^2 k_t. \tag{3}$$

The functional form of (3) consists of both fixed and smooth adjustment costs, (e.g., Cooper and Haltiwanger (2006)). The first two terms describe the fixed component, which allows firms to have asymmetric capital adjustment costs. c_{k1}^{-} represents fixed cost paid during the downward adjustment, and c_{k1}^{+} represents the cost under upward adjustment. The smooth component is captured by the third term, where c_{k2} is the parameter for the convex term and i_{it} denotes the capital investment. In the general case, c_{k2} and c_{k1} be dependent on the firm's share of each financing channel.

4.4 Financing constraints

As repeatedly mentioned in the previous section, due to the limited financing market accessibility, young firms, if they need funding, rely heavily on external debt financing sources. Unlike the previous models, I relax the single-channel assumption and allow firms to borrow from up to three channels: business bank loan, personal bank loan, and credit card borrowing.

4.4.1 Choices over three different channels

Among these three choices, business bank loans have lower risk and lower financing costs. This is because business bank loans are not backed by firm owners' personal wealth, which is the main collateral for personal bank loans. However, the main disadvantage of the business bank loan comes from the stringent requirement for application. For instance, to have a higher chance of qualifying for a business bank loan, the firm owner needs to maintain a good business running status and a higher credit record.

Personal bank loans and widely accessible credit card borrowing, on the other hand, do not have a complicated application and screening process. Specifically, the personal bank loan only needs firm owners' personal wealth as the collateral, and credit card borrowing often does not need any collateral. Hence, personal bank loans or credit card borrowing is much easier to obtain during firms' early development periods, along with a higher cost and risk than business bank loans. Nevertheless, firms can also choose self-financing to avoid the high bankruptcy risk and financing cost.

If a firm owner can borrow all they need from a business bank loan, she must have a lower risk and lower cost than another competitor who can only borrow from a credit card. Hence, the hierarchy is ranked from high to low as business bank loans, personal bank loans, and credit card borrowing. Since different channels have different interest rate requirements, a higher interest cost makes it costly to pay off the debt and raises young firms' future default risks. In this model, besides the direct borrowing limits from each channel, the weighted interest rate is an other implicit constraint that affects young firms' investment strategies.

4.4.2 Young firms' borrowing limits

Because of the limited accessibility and credit rationing, the borrowing limits of each channel will depend on the business status and characteristics, as well as the local financing supply shocks. In this model, firms are assumed to apply to all these channels at the beginning of each period. For notional convenience, I use subscripts b, p, c to represent business bank loans, personal bank loans, and credit card borrowing in the rest of the paper. First, credit card borrowing can be obtained directly but with a very high interest rate. Second, getting business bank and personal bank loans. However, firms have to search over the local financing market.

The searching process is organized as an open ascending auction with three stages. Firms will first start the search on the business bank loan sub-market. In the first stage, a firm will receive a take it or leave it offer from a bank, indicating the maximum borrowing amount, $\bar{h}_b$. $\bar{h}_b$ depends on the firm's current status plus the idiosyncratic financial market shock from business bank loans, denoted by ε_t^b. Once the offer is rejected, the firm will enter into the second stage and search over the local financial market, each bank will provide their maximum lending amount, $h_{b1}, h_{b2}, ...h_{bn}$, under the posted business loan rate. The quote follows

$$h_b \sim H(\cdot|\varepsilon_t^b, k_t, A, \lambda_t),$$

where λ indicates the firm's current credit record that will be explained later. According to the functional equation, a higher capital stock k_t, a better credit record λ_t, a higher type A, or a better shock ε_t^b will offer a firm a better quote. Then, in the final stage, the firm will collect all the quotes and select the one that grants the highest borrowing limit. But, it is also possible that the borrowing limit is zero. Because banks are assumed to be identical from each other, the first stage offer $\bar{h}_b$ is equal to the expected quotes of h_b when the information structure is symmetric:

$$\bar{h}_b = \mathbb{E}(h_b|\varepsilon_t^b, k_t, A, \lambda_t). \tag{4}$$

Similarly, the personal bank loan follows the same procedure except with shock ε_p:

$$\bar{h}_p = \mathbb{E}(h_b|\varepsilon_t^p, k_t, A, \lambda_t). \tag{5}$$

Then the borrowing limits from business or personal loans can be expressed as the function of $\varepsilon_t^b, \varepsilon_t^p, k_t, A, \lambda_t$. The above two equations plus the free accessibility to credit card borrowing construct the main financing constraints in this model. A firm can take any combination of business, personal or credit card borrowing channels to meet their financing demands. Because different channels have different interest rates, the combination of three channels will shift the weighted interest rate from low to high.

Additionally, firms can accumulate their credit record to increase their possibilities and borrowing limits for low cost channel, i.e., business loans. And usually if a firm successfully gets funding support from the business loans in this period, it is easier to get funding again in the future. To capture such feature, there is a Markov process λ tracking the firm's current credit level:

$$P(\lambda_{t+1}|\lambda_t, 1_{\{bus=1\}}). \tag{6}$$

The evolution of the firm's credit record is conditional on whether firms has business loans or not in this period. If the firm can get access to the business bank loan, then the firm has a higher probability of keeping or upgrading to the higher credit level in the next period.

4.4.3 Total borrowing amount and financing cost

After a firm owner learns her borrowing limit from the searching process, the interaction between a firm owner and a banker is summarized in the form of the debt contract. Given the next period investment plan, there could be multiple debt contracts for firms to choose from. Without loss of generality, let $\Omega(k_{t+1}, \mu, \lambda_t|A, \bar{h}_b, \bar{h}_p)$ be the set of debt schedules available to a firm, based on the setup in Arellano et al. (2012).

Besides borrowing limits, the borrowing decisions also depend on firms' default likelihood. For each loan contract (b_{t+1}, b_{t+1}^R), a banker transfers b_{t+1} to the firm today and receive b_{t+1}^R(interest + princpial) if firms repay, or W($\cdot$) if firms default next period. The liquidation value depends on the capital stock as well as the share of each channel's borrowing amount, denoted as $s_f, f \in \{b, p, c\}$. Different channels have different priorities for claiming the liquidation value. Debt schedules $\Omega(k_{t+1}, \mu, \lambda_t | A, \bar{h}_b, \bar{h}_p)$ include all contracts (b_{t+1}, b^R_{t+1}) that allow creditors to break even in expected value. For example, if the firm only takes business bank loan, then the new borrowing b_{t+1} and total payment in the next period b^R_{t+1} have the following equation:

$$b_{t+1} = \frac{b^R_{t+1}(1 - \mathbb{E}\chi) + \mathbb{E}_\chi[W(k_{t+1})]}{1 + r_b}. \tag{7}$$

$$b_{t+1} \leq \bar{h}_b$$

$$\mathbb{E}\chi = \mathbb{E}_{\lambda,\mu}\chi(k_{t+1}, b^R_{t+1}, \lambda_{t+1}, \mu_{t+1} | \lambda_t, k_t) \tag{8}$$

where χ represents the exit decisions, and r_b is the interest rate for business loans. 1-$\mathbb{E}\chi$ represents expected survival probability given current status. And $\mathbb{E}_\chi[W(k_{t+1})]$ represents the liquidation value that the banker can get if the firm goes bankrupt. If firms take multiple channels, then we can treat multiple channels as one unified channel with the weighted average interest rate for simplification. And the equation becomes:

$$b_{t+1} = \frac{b^R_{t+1}(1 - \mathbb{E}\chi) + \mathbb{E}_\chi[W(k_{t+1})]}{1 + \bar{r}(\xi, \bar{h}_b, \bar{h}_p, k_t)}. \tag{9}$$

$$\bar{r} = \sum_{f \in \{b,p,c\}} s_f r_f$$

where $s_f, f \in \{b, p, c\}$ represents the ratio of each channel and r_f $f \in \{b, p, c\}$ represents the average interest rate per channel. The left-hand side is the resources that creditors spend today. The right-hand side is the expected repayment discounted by each channel's loan rate and weighted by the default probability. Both survival probabilities and interest costs determine the availability and the terms of debt contracts.

Besides the debt payment, firms also have to pay adjustment costs when adjusting their debt in each period besides the debt payment. Following the literature setup, I assume the convex debt adjustment cost as follows:

$$C^b_t = c_{b0} 1_{\{b_t > 0\}} + c_{b1} \frac{b_t}{k_t} + \frac{c_{b2}}{2} \left(\frac{b_{t+1} - b_t}{b_t} \right)^2 b_t \cdot 1_{\{b_{t+1} > b_t\}}. \tag{10}$$

The first term indicates the fixed expense regardless of the current debt level. The higher the c_{b0}, the less willingness for firms to take debt. The second term links the firm's leverage ratio (total debt over capital) to the debt adjustment cost. c_{b1} can be either positive or negative. The last term represents the convex adjustment cost that firms need to take when increasing their debt ratio. In the later discussion, we see that the second term is crucial for generating the fluctuation of firms' debt-taking behavior.

4.5 Exit decisions

When a firm either fails to pay off the interest rate or finds it better to leave the market, the liquidation process will start as follows:

$$
\begin{aligned}
V_{exit} &= \max\{\max\{\max\{W - s_b b_t, 0\} - s_p b_t, 0\} - s_c b_t, 0\} \\
&\quad s.t. \\
&\quad W = \kappa \cdot (1-\delta) k_t - c_{k1} k_t
\end{aligned}
$$

where s_f denotes the share of borrowing from channel f. After paying off the interest and leverage cost, the firm will use the remaining value to clear each channel's outstanding debt. Different channels have different priorities for claiming the liquidation assets. The ranking follows business bank loans, personal bank loans, and credit card borrowing. For example, if a firm takes both business and personal bank loans and the total repayment exceeds the resale value W, the firm will first use the resale value W to cover the business bank loan repayment. The left value will go to the personal bank loan. The uncovered part becomes the loss of the creditors.

4.6 Maximizing firm value

Until now, the main components of the model have been described. To construct the young firm's Bellman equation, we first need to specify the firm's state space, $\boldsymbol{X}$. First, firms make decisions based on current capital stock k_t and total debt repayment b_t^R. The exogenous state variables include $(\varepsilon_t^b, \varepsilon_t^p, z_t)$ plus the transitional state variable λ_t. So the conditional state space is summarized by $\boldsymbol{X}_t = \left\{k_t, b_t^R, z_t, \varepsilon_t^b, \varepsilon_t^p, \lambda_t\right\}$. Additionally, firms are conditioned by their characteristics A.

Given current state variables, young firms make intertemporal capital investment and borrowing decisions to maximize the discounted sum of future profits. Regarding the exit conditions, the firm owner will compare the exit value, $V_{exit}(\boldsymbol{x}_t|A)$, with the continuation value. If the firm value is below the exit value, the firm will leave the market. Otherwise, the firm will move into the next period. The Bellman equation can be expressed as:

$$V(\boldsymbol{x}_t|A) = \max\left\{V_{exit}(\boldsymbol{x}_t|A), \max_{k_{t+1},(b_{t+1},b^R_{t+1})\in\Omega(k_{t+1})}(1-\tau)E_t + \tau\delta k_t + \beta\mathbb{E}V(x_{t+1}|A,\lambda_t)\right\}$$

$$s.t.$$

$$E_t = \pi_t + b_{t+1} - b^R_t - i_t - C^k_t - C^b_t \tag{11}$$

$$i_t \le \pi_t + b_{t+1} - (1+r_t)\cdot b_t - C^k_t - C^b_t \tag{12}$$

$$b^R_{t+1} \le \mathbb{E}[\pi_{t+1} + \kappa(1-\delta_k)k_{t+1} - c^-_{k1}k_{t+1} - c_{b1}\frac{b^R_{t+1}}{k_{t+1}} - c_{b0}] \tag{13}$$

and(2), (3), (4), (5), (10),

where β is the firm's discount factor,τ is the average tax rate for firms, and $(1-\tau)E_t$ is the retained earning for firm owners. If $V(\boldsymbol{x}|A) = V_{exit}(\boldsymbol{x}_t|A)$, the firm will exit the market and start the liquidation process. Otherwise, the firm will make new investment and borrowing decisions and move into the next period. Two more constraints are considered here. First, nonnegative earnings constraint in (12) indicates that young firms do not consider equity financing, and financing feasibility constraint in (13) restricts the total financing cost should not exceed the expected liquidation value of the next period. The details of optimal firm decisions will be discussed in the next subsection.

4.6.1 Firm behavior for investment and borrowing

To understand how young firms' financing decisions interact with their investment plan and their future growth paths, we can start from the situation without any binding constraints. For notational convenience, I drop the time index and denote the next period as prime ($\prime$) in the superscript of the state variables.

Capital investment Firms can both upward and downward adjust their capital stock. More specifically, given the current revenue realization, firms can either invest more to earn higher revenue in the next period or resale part of the capital and reduce the outstanding debt level. Firms make trade-offs between downward and upward adjustments depending on the leverage ratio (defined as debt over capital) and current capital stock. From the first-order condition on k', if the firm upward adjusts capital stock, we will have

$$\psi^k + c_{k2}\left(\frac{k'}{k}\right) = \beta\mathbb{E}[\frac{d\pi}{dk'} + \frac{c_{k2}}{2}\left(\frac{k''}{k'}\right)^2 + \underbrace{\frac{c_{b1}}{k'}[\left(\frac{b^R}{k'}\right) - 2\frac{db^R}{dk'}]}_{\text{marginal leverage discount}}, \tag{14}$$

$$\psi^k = 1 - \beta c_{k1} - (1-\delta)(\beta + \beta c_{k2} - c_{k2})$$

The third term on the right side of equation (14) is defined as the marginal leverage discount. Given the funding amount b', the more resources put into the capital accumulation, the less leverage discount in the future. Similarly, reducing the outstanding debt will help firms save the financing cost under good economic status. Thus, after growing into the desired size, young firms have the incentive to reduce their outstanding debt amount. On the other side, if a firm keeps being hit by bad shocks, the owner has to resale part of their assets to avoid liquidation to cover the expenses and costs. Under this scenario, the leverage discount is even more crucial for the firm's survival status, as shown in the following equation:

$$1 - \beta c_{k1} - (1-\delta)\beta = \beta\mathbb{E}[\frac{d\pi}{dk'} + \underbrace{\frac{c_{b1}}{k'}[\frac{b^R}{k'} - 2\frac{db^R}{dk'}}_{\text{marginal leverage discount}}], \tag{15}$$

Because the left-hand side is a constant, whether the equality holds or not depends on the changes of the leverage discount and current capital stock. The heavier the leverage a firm has, the higher the exit hazard that a firm takes. The firm's capital structure, if c_{b1} is not trivial, acts as an accelerator that amplifies the firm's growth dynamics: either successfully grow large or go bankrupt and exit the market.

Financing choices with multiple funding channels The previous discussion focuses on the impact of a firm's financing on investment decisions. When making new borrowing decisions, firms need to make trade-offs between having more current funding sources and bearing more future financing costs. Apart from the interest cost, increasing the debt-taking amount also increases the hazard rate for the failure in the future, which the lenders will further increase the cost of financing. From equation 7 and 8, we can see clearly how the exit probability affects the total financing cost

b^R.From the first-order condition on new debt b', When firms increase their borrowing amount

$$\psi^b - c_{b2}\frac{b'}{b} = \beta\frac{db^R}{db'}\mathbb{E}\left[2c_{b1}\frac{1}{k'} - \frac{c_{b2}}{2}\left(\frac{b''}{b^R}\right)^2\right]. \tag{16}$$

$$\psi^b = 1 + c_{b2} - \beta\frac{db^R}{db'}(1 + c_{b2})$$

Affected by the expected survival rate and each channel's interest cost, The combinations of different funding channels will result in different optimal borrowing amounts. To simplify the analysis, we assume the firm's exit probability and liquidation value is fixed. Then, $\frac{db^R}{db'}$ is a constant term that is only correlated with the interest rate for different channels.

As shown in the figure 9, at the optimal point, firms will increase the borrowing amount if they can borrow from the low-cost channel (e.g., the business bank loan). Firms with good credit records and relatively high capital stock have higher chances to access business loans. Business loans, in turn, help those firms maintain higher credit records and earn higher revenue. Such a positive feedback loop accelerates the capital accumulation during their early development periods. On the other side, when borrowing from the high-cost credit card channel at early periods, firms often have to use a significant share of their revenue to cover the cost of the expenses and financing. Under this situation, the high financing cost and operational expenses eat up the firm's resources for capital accumulation.

Firms often rely heavily on external financing to continue their business. A key question in financing decisions is finding the optimal leverage ratio that balances future growth and potential risks. In a frictionless environment where we ignore exit probability, i.e. $b^*_R = (1+r)b^*$, we can see how a firm's leverage is correlated with their expected revenue and capital stock from the feasibility constraint:

$$\frac{b^*}{k^*} = \frac{1}{1+r}\mathbb{E}[\pi + \kappa(1-\delta_k) - c_{k1} - c_{b1}(1+r)\left(\frac{b^*}{k^{*2}}\right)],$$

$$\frac{b^*}{k^*} = \frac{1}{(1+\frac{c_{b1}}{k^*})}\frac{1}{1+r}\mathbb{E}[\pi + \kappa(1-\delta_k) - c_{k1}]$$

where k^* and b^* represent one pair of capital and debt combination that binds the feasibility constraint in equation (13). From the equation, we see that credit costs make small firms more constrained than large firms. The disproportionate financing risk between big and small firms leads to heterogeneous long-run growth paths: firms who want to grow big may take risky investments and borrow heavily even if the current revenue is not good enough. If they do receive a good revenue realization, optimal choices for small firms may reduce the leverage and save the financing cost payment in the future.

5 Identification and Estimation

Since the model is a nontrivial combination of a firm's financing decisions and dynamic growth pattern, to estimate the model, we need a proper estimation strategy for recovering the young firm's cost structure, especially on the financing decision part. The identification and estimation procedure can be divided into two stages. In the first stage, I estimate the firm's borrowing limits and revenue function by applying the indirect inference method. After getting the first stage estimators, I can further recover the cost structure in the second stage with the simulated method of moments. Then, the estimated policy function will help to simulate the data in the first step again and repeat the first and second steps until the estimation results converge. I will address each of them in the rest of this section.

5.1 First step: recovering the revenue function and borrowing limits

Young firms need to learn the borrowing limit functions for business and personal bank loans. But what we can observe is $b_{tf}, f \in \{b, p\}$, not the real limit, $\bar{h}_f$. To help establish the borrowing limit function, we need to take advantage of the multiple choices of external channels made by the young firms. The econometric specification is assumed to follow (subscript i represents the individual firms.)

$$h^*_{ibt} = \gamma^b_0 + \gamma^b_1 k_{it} + \gamma^b_2 A_i + \gamma^b_3 \lambda_{it} + \varepsilon_{ibt}, \tag{17}$$

$$h^*_{ipt} = \gamma^p_0 + \gamma^p_1 k_{it} + \gamma^p_2 \alpha_{it} + \gamma^p_3 \alpha_{it} k_{it} + \gamma^p_4 A_i + \varepsilon_{ipt}, \tag{18}$$

$$h_{ift} = \max\{h^*_{ift}, 0\}, \quad f \in \{b, p\}$$

where $\alpha_{i,t}$ denotes whether firm i at time t get the business bank loan or not. The distributions of financing shock ε_b and ε_p are assumed to follow i.i.d. mean zero normal distribution with variance σ^2_b and σ^2_p. Similarly, the firm's revenue function can be defined as

$$y_{it} = ROA(k_{it}, A_i, \alpha_{it}, \mu_{it}) = \phi_0 + \phi_1 k_{it} + \phi_2 k^2_{it} + \phi_3 A_i + \mu_{it}. \tag{19}$$

Again, the idiosyncratic shock μ_t follows normal distribution with variance σ^2_μ. The key challenge here is that we cannot directly observe the borrowing limit h and the firms revenue can be potentially left censored. Therefore, I need simulation method to help me recover the set of coefficient $\Theta = \{\gamma^b, \gamma^p, \phi\}$.

Algorithm for estimation In order to map the model to the data, I adopt the indirect inference method in the first step. The idea is that the simulated data generated by the true parameter Θ^0 should keep the same features as the real data. In other words, if we specify a random econometric model, when we run the regression with the real data and simulated data, the two estimated results should be no statistical different from each other. To do so,

1. I use the data to run the regression based on the following econometric specifications auxiliary models for borrowing limits and revenue function, respectively.

$$
\begin{aligned}
b_{bt} &= \bar{\gamma}_0^b + \bar{\gamma}_1^b k_{it} + \bar{\gamma}_2^b A_i + \bar{\gamma}_3^b \lambda_{it} + \varepsilon_{ibt}, && (20)\\
b_{pt} &= \bar{\gamma}_0^p + \bar{\gamma}_1^p k_{it} + \bar{\gamma}_2^p \alpha_{it} + \bar{\gamma}_3^p \alpha_{it} k_{it} + \bar{\gamma}_4^p A_i + \varepsilon_{ipt}, && (21)\\
y_{it} &= \bar{\phi}_0 + \bar{\phi}_1 k_{it} + \bar{\phi}_2 k_{it}^2 + \bar{\phi}_3 A_i + \mu_{it}, && (22)
\end{aligned}
$$

   and get the coefficients of the explanatory (state) variables, denoted as $\Xi^d = \{\bar{\boldsymbol{\gamma}}^b, \bar{\boldsymbol{\gamma}}^p, \bar{\boldsymbol{\phi}}^s\}$[10]. For example, I run the ordinary least square and Tobit model for each of the three channels.

2. Then, based on the empirical distribution of these idiosyncratic shocks learned from the data, I use the model to simulate a set of data. The set of parameters used for simulation is denoted by $\Theta_s^0 = \{\gamma^b, \gamma^p, \phi\}$. Then I apply the simulated data to run the same auxiliary models, (20), (21), and (22) again and obtain the simulated coefficients, denoted as $\Xi^s = \{\bar{\boldsymbol{\gamma}}^s, \bar{\boldsymbol{\gamma}}^s, \bar{\boldsymbol{\phi}}^s\}$

3. I repeat the first and second steps to compare Ξ_1^d with Ξ^s . The algorithm is designed to search the optimal parameters $\hat{\Theta}$ so that simulated moments can be as close as possible with the data moments. And the estimates $\hat{\Theta}$ is saved as the first stage parameters.

Specifically, (20), (21), and (22) construct the auxiliary model, denoted by $J(\boldsymbol{x}, \Xi)$. By optimizing $J(\boldsymbol{x}, \Xi)$ using the real data and simulated data, we get $\Xi^d$and Ξ^s by the following objective functions,

$$
\begin{aligned}
\Xi^d &= \arg\max_{\Xi} J(\boldsymbol{x}, \Xi^d),\\
\Xi^s(\Theta) &= \arg\max_{\Xi} J(\boldsymbol{x}^s, \Xi^s(\Theta)).
\end{aligned}
$$

[10]The bold parameters indicates the vector list. For example, $\bar{\boldsymbol{\gamma}}^b = \{\bar{\gamma}_0^b, \bar{\gamma}_1^b, \bar{\gamma}_2^b, \bar{\gamma}_3^b\}$

The indirect estimator of Θ is then defined as the solution to the minimization of

$$\hat{\Theta} = \arg\min_{\Theta} \left[\Xi^d - \frac{1}{S}\sum_{s=1}^{S} \Xi^s(\Theta) \right]^T \hat{W}^d \left[\Xi^d - \frac{1}{S}\sum_{s=1}^{S} \Xi^s(\Theta) \right], \tag{23}$$

where $\hat{W}^d$ is a positive definite (weighting) matrix that can be obtained from the inverse of the covariance matrix of data moments. The indirect inference method is a special case of the simulated method of moments where the moments that we use come from the auxiliary model. The advantage of applying indirect inference is that the set of equations (17),(18), (19), naturally can be the auxiliary model and is easy to compute. After getting the estimated $\hat{\Theta}$, we can work on the structure estimation for the cost structure in the second step.

5.2 Second step: backing out cost structure

The firm's cost structure affects the dynamic investment and financing decisions. Therefore I have to solve the Bellman equation and apply the simulated method of moments(SMM), which chooses model parameters that set moments of artificial data simulated from the model as close as possible to corresponding real data moments. There are two sets of cost parameters waiting for estimation in the second stage. The capital adjustment cost include the fixed and smooth part c_{k1} and c_{k2}. Moreover, c_{k1} is allowed to be different from upward (c^+_{k1}) and downward (c^-_{k1}) adjustment. In the debt part, to match the data better, besides the c_{b1}, and smooth part c_{b2}, I also include the fixed debt taking cost c_{b0} indicating that maintaining outstanding debt is costly in each period. The sets of the second stage estimators are denoted by $\mathit{\Theta} = \{c^+_{k1}, c^-_{k1}, c_{k2}, c_{b0}, c_{b1}, c_{b2}\}$. Additionally, in the baseline estimation, I fix the external environment parameter $\xi = 0$.

The goal is to estimate $\mathit{\Theta}$ by matching a set of simulated moments, denoted as $\mathit{\Psi}^s(\mathit{\Theta})$, with the corresponding set of actual data moments, denoted as $\mathit{\Psi}^d(\boldsymbol{x})$. Define

$$g_n(\mathit{\Theta}) = \frac{1}{n}\sum_{i=1}^{n} \left[\mathit{\Psi}^d(\boldsymbol{x}) - \frac{1}{S}\sum_{s=1}^{S} \mathit{\Psi}^s(\mathit{\Theta}) \right]$$

The estimator of $\mathit{\Theta}$ is then defined as the solution to the minimization of

$$\hat{\mathit{\Theta}} = \arg\min_{b} g_n(\mathit{\Theta})^T W_n g_n(\mathit{\Theta}), \tag{24}$$

where W_n is the weighting matrix. Following the literature approach, I use the inverse of the sample covariance matrix to approximate W_n. The success of the SMM relies on picking moments $\mathit{\Psi}$ that can identify the structural parameters Θ. The global identification obtains when the expected value of the difference between the simulated and data moments equals zero if and only if the structural parameters equal their true values. An ideal moment selection is the establishment of a one-to-one mapping between the structural parameters and a subset of the data moments of the same dimension. To avoid getting local minimal, I refer to the simulated annealing method for minimization.

To estimate these parameters, I use the capital and debt adjustment ratio, firm's leverage, firm's capital level, and outstanding debt level as the key moments for estimation. I also include the average firm's asset and debt level to match the data. The mean value of the downward and upward capital adjustment ratio helps to pin down the capital adjustment cost, $c_{k1}^{+}, c_{k1}^{-}, c_{k2}$. The level of the c_{k1}^{-} directly affects the downward adjustment ratio. On the other side, the upward adjustment ratio is affected by both the c_{k1}^{+} and c_{k2}.

In the debt adjustment part, the value of c_{b0} directly affects young firms' intensive margin of taking debt or not. Additionally, both the downward debt and capital adjustment cost is impacted by c_{b1}. The smooth part, c_{b2}, directly affects the upward debt adjustment ratio. Moreover, as c_{b2} increases, borrowing more new debt becomes costly, affecting the leverage ratio.

After getting $\hat{\Theta}$, we can then calculate the optimal policy and go back to the first step and start the estimation procedure again until both objective functions (23),(24) achieves the optimal simultaneously.

5.3 Predetermined parameters

Apart from the model parameters for estimation, some predetermined parameters that are obtained directly from the data and literature such as time discount β, depreciation rate δ, capital resale discount κ, local posted interest rate R_b, R_p, R_c and average tax burden for firms τ. The β is set to 0.95. I choose δ equal to 0.15, the same as DeAngelo et al. (2011). The capital resale discount κ is obtained from Khan and Thomas (2013) which is equal to 0.954. I use the average posted interest rate data from Rate-watch, and the financing cost for each channel is 1.046,1.087,1.176, respectively. And the tax rate for the company is set to 0.2 from Belo et al. (2019). Table 8 lists the calibrated parameters specification.

5.4 Model estimation

5.4.1 First stage estimation results

The estimation results of the revenue function and two borrowing limits are listed in table 9, 10, and 11, respectively,

From the results, we see that most simulated moments have a good approximation for the data moments. In table 9, the revenue function estimation, one moment, the type indicator, has some distance away from the corresponding value in the data. Since the type indicator, A, is constructed by the observed characteristics, it may not capture all the factors that affect the young firm's revenue. The type indicator does not affect the curvature of the revenue function. The optimization decision of firms' investment and borrowing should not be seriously affected. A potential caveat is the underestimation of the difference between low and high types.

In the revenue function, the significance of ϕ_2 justifies the concave property of the revenue function in the model, and the firm's credit record, λ, does affect the firm's profitability. According to the estimation, getting a high-level credit record is equivalent to having extra 0.3 capital stock for a young firm. When firms are small, this extra increment is crucial for revenue earning.

In the borrowing limit of business and personal loans (table 10 and 11), the coefficient in front of the type indicator, γ_2^b and γ_4^p, shows that high-type firms can get more line of credit from business loans but less from personal loans. This means that high-type firms are professional in utilizing business loans for their businesses. Personal loans, on the other hand, are more favored by low-type firms. The coefficient of the capital stock, or the collateral ratio, is similar between business and personal. One extra capital stock can be backed for 0.63 with business loans and 0.65 with personal loans. The negative sign of γ_3^p implies the substitution pattern between business and personal loans, which is consistent with the empirical fact. Additionally, the borrowing limit of personal loans is not correlated with the credit record λ since personal loans are backed by the firm owner's personal wealth and personal credit scores, not the firm's credit record[11].

[11] Notice that when simulating the data, we ignore the dynamic changes over time. A potential caveat of this simplification is the autocorrelation from the productivity shock. By checking on the regression residuals from the data, I found the residual series have the autocorrelation with $\rho = 0.057$. Considering the size of the autocorrelation and its impact, I decided to ignore the autocorrelation in the estimation process. In the robustness check, I find that adding the autocorrelation will not have a significant influence on the first stage estimation results.

5.4.2 Second stage estimation results

Because there are two types of firms in this model, I estimate the cost structure for high and low-type firms separately. And the estimation results are shown in the table 12 and 13, where panel A indicates the moment matching and panel B displays the estimates.

The simulated moments, in general, are close to the data moments. One exception is the debt amount, where the model predicts a lower debt-taking amount than the data. One reason is the logarithm transformation of capital and debt results, marking a firm's leverage much higher after the logarithm transformation. Still, the model managed to match the capital level for debt and non-debt firms. One success of this model is to keep the ordering of the debt and non-debt firms' adjustment ratio in the simulated moments where both downward and upward adjustment ratios of debt firms are smaller (in absolute value) than the non-debt firms. It is also interesting to find that high-type firms' capital and debt adjustment ratios are smaller than low-type firms. Regarding the big firms in high-type firms, high-type firms' long-run growth paths are more stable than low-type firms.

The estimation results show that both high and low-type firms bear nontrivial capital adjustment costs. Compared with low-type firms, high-type firms face a lower fixed capital adjustment cost. Heuristically speaking, high-type firms should have better management skills for organizing production, which results in a lower fixed cost, especially during the expansion period. The gap of the convex component between low and high types is small. Although not entirely comparable with other papers that use different datasets, the convex component of the capital adjustment cost is relatively heavy for young firms.

In the debt adjustment part, although taking debt has to pay the fixed cost. The negative sign ofc_{b1} illustrates that firms with higher leverage (defined as debt to assets) can offset the cost payment. Because low-type firms have a higher fixed component of debt burden, c_{b0}, the benefit of maintaining a high leverage ratio is much smaller, as shown in the value of c_{b1} for low-type firms. In terms of the convex component, adjusting debt is also more costly for low-type firms. Compared with low-type firms, high-type firms are better at utilizing financing sources to support their development.

6 Comparative Statistics: Illustrations on Estimation results

This section provides some intuitive explanations to illustrate the connection of cost structure with young firms' financing and investment decisions.

6.1 Distributional effects on firm's financing decisions

Figure 10 and 11 display the firm capital size distribution for low-and high-type firms. It is clear that debt firms, on average, are larger than non-debt firms. However, debt firms are also skewed at the bottom tile of the distribution. Regarding the firm's financing decisions, young firms of different sizes or types can have different financing decisions. To see this, I decompose the firm capital size distribution and see how debt-taking behavior varies across firms in different percentiles. Table 14 reports the average debt-taking ratio, business debt-taking ratio, and capital level for debt and non-debt firms across the distribution after early-period development—panel A and B list the results of low and high types respectively.

Table 14 yields several interesting findings. First, firms' debt-taking behavior has the U-shape changes across the capital distribution for both low and high types. This shows that not only large firms at the top of the distribution, firms at the bottom tile of the distribution, i.e., $<$10%,$<$25%, also rely on external financing sources heavily. When small firms grow large, their leverage ratios first decrease then increase. Second, for business loans, the bigger the size, the higher the probability of firms taking. Third, debt firms below the median of the distribution have a smaller capital level than non-debt firms in the high-type group. In other words, the capital level of debt firms does not monotonically dominate non-debt firms. Additionally, For low-type firms, the gap of capital stock between debt firms and non-debt firms is smaller when firms are below the median of the distribution.

Together, these findings indicate that the firms have different financing strategies across the capital size distribution and their types. Although the model underestimates the debt-taking amount, debt firms on the bottom of the distribution, i.e., $<$10%,$<$25%, typically maintain a high leverage ratio. Under the estimated cost structure, small firms tend to reduce the debt level to avoid high-cost payments when making new investment and borrowing plans, explaining the U-shape debt-taking ratio and smaller capital stock.

6.2 Impact from the capital cost structure

Depending on the cost structure, debt firms can either expand their businesses by taking more debt or pay off the outstanding debt and reduce the debt burden in the future. This section further illustrates the impact of cost structure on young firms' financing choices and their growth pattern. To do so, I analyze the model for a range of parameters value around the baseline value of adjustment cost, typically from the capital adjustment part. Furthermore, I present model predictions regarding the impact of capital cost structure on future capital accumulation and debt-taking ratio.

To obtain comparative statics results, I start with the baseline parameter values (from estimation) and analyze the model for a significant range of parameter values around each baseline value of the capital cost structure. Specifically, I shift the parameter values for c_{k1}^{+}, c_{k1}^{-}, and c_{k2}.I run the model by combining any two of them and checking the average long-run capital level and debt-taking ratio changes, respectively.

Table 15 and 16 report the average future capital level and financing decisions as a function of c_{k1}^{+} and c_{k1}^{-} under low and high types, respectively. The columns indicate the changes of downward adjustment fixed cost,c_{k1}^{-}, from low to high. The rows within each panel indicate the changes of upward adjustment fixed cost,c_{k1}^{+}, from low to high. From panel C and D, we see that the relative size between debt firms and non-debt firms is sensitive to the fixed capital adjustment cost changes. When firms have a lower downward adjustment cost, i.e., c_{k1}^{-} is small, non-debt firms have higher capital levels than debt firms. This implies that firms do not have to resale a large fraction of their capital stock to pay the adjustment cost during the downward adjustment situation. On average, their capital accumulation speed is faster than before. The reliance on external debt is reduced. Those who need external debt to help them maintain the business and pay the adjustment cost often experience a large downward adjustment, which is smaller and slower for recovery in the future. Under this scenario, there is an adverse selection for seeking financing support, resulting in the reversal pattern between debt firms and non-debt firms. And the results hold for both types of firms.

On the other side, changes in the upward adjustment cost do not flip the dominant pattern between debt firms and non-debt firms. The increment of the c_{k1}^{+} will make it harder for firms to accumulate their capital, which impairs firms' long-run growth potential. This holds for both types of firms. The convex component has the similar results in firms' long-run capital accumulation, shown in table 17 and 18. The shifting convex component affects the capital accumulation level for debt and non-debt firms in the same direction. Intuitively, firms, regardless of taking debt, all find it costly to expand their businesses when convex component adjustment cost increases. However, because of the property of the convex form, firms with higher capital stock are less costly to adjust their capital compared with small firms. If debt firms are on average bigger than non-debt firms, increasing the convex component of the capital adjustment cost will also enlarge the gap of capital level between debt and non-debt firms. Regarding the debt-taking ratio, the higher the c_{k1}^{+} is, the more firms choose to seek external financing. Since firms need extra funding resources to compensate for the increasing fixed cost, this relationship is reversed for the convex component.

7 Comparative Statistics: Young Firms' Financing Behavior and Growth Opportunities

This section predicts how a young firm's future growth path is affected by their early period financing behavior. For example, getting a low-cost channel helps firms build growth advantages initially and accumulate more capital in their early development stages. On the other side, if a young firm uses a high-cost funding channel and does not receive a high revenue realization, firms have to resale part of the capital stock to cover the loss and expenses, slowing down the average growth rate of the cohort.

In this part, I modify the early period external financing accessibility to see how young firms' average growth rates (measured by capital accumulation) correlates with the choices of different funding channels. Specifically, I test how the variation of borrowing limit in each channel affects young firms' long-run growth path. To compare the experiment with the baseline model, I use the same cost structure and exogenous shock parameters as the baseline model except for the financing shock. Blocking one of the three main channels means that none of these young firms can access that funding channel for the rest of their lives. Through this experiment, we can learn the direct impact of that particular channel on a firm's long-run growth path.

7.1 Impact of accessing to credit: Overview

Figure 12 shows the changes in debt-taking ratio and average assets level when we block the business loans and personal loans for low-type firms at the entry stage. From the table, blocking business loans insignificantly impacts the firm's average long-run capital level as a debt-taking ratio. Similar things happened in blocking personal loans. The results imply that the financing gap caused by bank loans can be quickly filled up by unlimited credit card borrowing. However, as the financing cost increases, the nearly identical outcomes from the debt-taking ratio indicate that low-type firms still borrow the same amount of money as the baseline case. The optimal borrowing amount still holds the same as before, only needs to pay higher financing cost for now.

In contrast, access to business loans is important for high-type firms debt taking behavior and long-run capital accumulation, as shown in figure 13. Based on the model framework, we learn that getting business loans has a positive feedback loop that boosters the growth rate. Compared with low-type firms with less than 15% having business loans, 50% of high-type firms can get business loans. Hence, the negative impact on the long-run growth potential is more noticeable. Regarding the distributional effect, the decline of the growth potential occurred throughout the whole distribution. On the other hand, the debt-taking ratio is much less affected for firms with smaller sizes (i.e., below the median of the size distribution). Instead of seeking more credit card borrowing for substitution, big firms tend to save their retained profits for investment, reducing the debt-taking ratio and total debt amount. Unlike low-type firms, the increasing financing cost from the substitution strategies will shift high-type firms' optimal investment strategies from borrowing to non-borrowing.

If credit card borrowing is blocked, credit card borrowing will no longer be the last resort for firms seeking financing support. Figure 14 reports the trend of the average debt-taking ratio by blocking credit card accessibility for low-and high-type firms. Figure 14 shows that losing access to credit card borrowing will lead to a shortage of funding supply. However, the blocking affects not just firms with only credit card borrowing. The ratio of taking other channels also drops sharply, resulting in a deep decline in the total debt-taking ratio for both types. The debt-taking ratio from both types drops to zeros after three years of development. Such finding indicates that young firms make lumpy financing decisions. When the financing support can not satisfy the target borrowing amount, young firms will turn to self-financing instead of reducing the total debt financing amount.

Unlike blocking business or personal loans, removing credit card borrowing will also affect non-debt firms' future growth paths. However, as shown in figure 15 , different types of non-debt firms have heterogeneous reactions. When credit card borrowing is blocked, non-debt firms from high-type groups experience a sudden drop in the average capital level, and the gap persistently exists in the long run. Non-debt firms with low-type, on the other hand, grow a little higher after the credit card channel is shut down. Such increment may come from the fact that many large firms turn to self-financing instead. The different growth patterns of non-debt firms show that without enough financing support, a majority of high-type firms can not maintain a high level of capital stock. As a result, many firms get trapped into the small size and are constrained to grow big.

In contrast, although previous debt firms now become non-debt firms in the low-type group, the average capital level is not significantly different from the baseline case. This means debt firms and non-debt firms have a similar firm size distribution ex-ante. When removing the financing support, debt firms with high-type are even smaller than non-debt firms. In terms of policy perspective, relaxing the financing constraints for typical high-type firms will have better policy rewards than helping a low-type counterpart.

7.2 Impact of accessing to credit: limit in credit card borrowing

The variation in the intensive margin of financing raises a new question about the relationship between borrowing limits and firms' investment and borrowing decisions. To answer this question, I further test the firm's financing behaviors and economic performance by imposing different levels of borrowing limits for credit card borrowing. For high-type firms, the maximum borrowing limit from the credit card channel is set to $\{4, 3, 2, 1\}$. For low-type firms, the limit ranges from $\{2.5, 2, 1.5, 1.25, 1\}$. The motivation of the range is to match the average total borrowing amount of two types groups.

The counterfactual results are listed in figure 16 and 17 for low-and high-type firms respectively. We see that as the borrowing limit of the credit card declines, the outstanding debt amount and capital level for debt firms decrease monotonically. On the other hand, the average debt-taking ratio is relatively stable when borrowing limits are not too constrained for young firms.

Table 19 and 20 shows the distributional effects of limited credit card borrowing on different types of firms' financing decisions. We see that in the long run (after six years of development), more firms at the bottom tile (<25%) seek financing support, i.e., credit card borrowing, and fewer firms at top tile(>75%) maintain a positive leverage ratio. Such distributional patterns shift the firm size distribution to the left and make the distribution of the cohort more extreme. As the borrowing limit becomes increasingly strict, small firms are getting harder to cover the firm's financing demand from the external financing channels. Instead of borrowing up to the limit, firms would rather not borrow and accumulate their retained profit for future development. Third, both low and high-type firms keep the same direction for the changes in the debt-taking ratio and the capital accumulation level. Due to the difficulty in accessing business and personal loans, low-type firms are more easily constrained by the limit in credit card borrowing.

Consistent with the previous part, young firms' extensive margin of financing decisions at different percentiles drive their growth patterns. The debt-taking ratio, in turn, depends on the borrowing limits of available financing channels. When a firm's financing sources cannot cover the financing demand, instead of borrowing to the limit, the firm often chooses not to borrow. Hence, to help young firms grow and survive, probably expanding their external financing options is better than lowering the interest rate for a small set of hard-to-access financing channels.

7.3 Impact of accessing to credit: direct effect of different channels

The previous sections show how young firms' access to different channels affects aggregate outcomes, such as debt-taking ratio and long-run capital level. Since the substitution effects and the optimal financing decisions are at an extensive margin, it is hard to see the direct relationship between getting one specific channel and its future growth path. In this part, I zoom into the subgroups of those firms who get the particular channel initially and see how these firms evolve over time when there is a shock or constraints on the access to that channel.

The experiment starts with the baseline model. I track firms' best financing channel f, $f \in \{\text{bus, pers, creditcard}\}$, that they receive at the initial period. Then I rerun the simulation by setting the restrictions on channel f' (f'can be different from f) and measure the difference between the two situations. By comparing the difference of the long-run growth paths, we can learn the causal effect of channel f for different types of firms under different financing market fluctuations. Figure 18 plots the causal effect of getting business bank loans, personal loans, and credit card borrowing, respectively, on young firms' capital accumulation path under different financing environments.

In figure 18a, we see that low firms that get business loans are those large firms at the starting point. Over time, having business bank loans for these firms does not further increase their growth potential. Both the business and personal loans have little impact on low-type firms' future growth paths. Blocking either business or personal loans does not have any salient influence on firms' future growth paths. Blocking credit card borrowing, however, does lower young firms' long-run capital level regardless of what they take at the beginning, as shown in figure 18e. Firms that receive business loans initially have smaller downward adjustment ratios than the other two cases. Even getting access to business or personal loans, bank loans only account for one-quarter of the total borrowing amount. It is credit card borrowing that dominates the low-type firm's debt-taking behavior.

The results for high-type firms are shown in figure 18b, 18d, and 18f. Having business bank loans at the initial period does increase firms' future growth paths, though not much. The effect of personal loans is also bigger than low-type cases. The young firm's future growth trajectory experiences a sharp decline when credit card borrowing is blocked: borrowing from bank loans can not cover young firms' funding demand.

The findings in this part reinforce the critical role that credit card borrowing played in firms' early development periods. Credit card borrowing represents any form of debt financing channel that is easy to access to young firms. The growth accelerator of getting business loans also relies on free accessibility to credit card borrowing. Facing the shortage of financing supply, even though having business loans, young firms still get trapped in a low long-run growth path. Firm owners' heterogeneity further strengthens the impact: the positive effect of having business loans is insignificant in the low-type group.

8 Changes in the External Financing Environment and Young Firms' Long-run Growth Patterns

8.1 Financing cost and bank industry consolidation

Firms' financing conditions are closely correlated with the local financial market. When studying the impact of the financial market on firms or household behavior, the literature often follows the conventional assumptions that financial intermediaries are perfectly competitive. However, the bank industry in the US is among the top sectors with frequent merger and acquisition (M&A) activities. Starting in the 1990s, with the relaxing of state and federal restrictions on banks activities[12], the bank industry consolidation has moved in the new phase, and we have witnessed the increasing concentrated bank industry over the past two decades. For example, the asset market share of the largest five US banks rose from 26% in 1996 to 50% in 2018. Figure 19 lists the trend for mergers and the number of commercial banks in the past two decades. Since 2000, the commercial banks have experienced three waves of M&As, and in 2020 the total number of commercial banks reduced by nearly 50% compared with the number in 2000.

An oligopolistic bank industry will have quite a different implication on the firm dynamics. One of

[12] Among all the relaxation practices, two acts are worth mentioning. First, the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 allowed banks to branch interstate by consolidating existing out-of-state bank subsidiaries or acquiring banks or individual branches through mergers and acquisitions. Second, President Clinton signed the Financial Services Modernization Act in 1999 allows banks to merge with securities firms and insurance companies within financial holding companies.

the direct impacts is on the firm's financing cost. By regressing the proxies of the local financing environment on the interest rate for each financing channel, we can see how the local financing cost reacts to the local bank consolidation process. The specification is detailed in the following:

$$\bar{r}_{g,f,t} = a_0 + \beta_1 HHI_{g,t} + \beta_2 Deposit_{g,t} + \beta_3 N_{g,t} + \delta_g + \tau_t + \varepsilon_{g,t}, \tag{25}$$

where subscript g denotes the geographic level either MSA or county level; f denotes the channels: business bank loan, personal bank loan or credit card borrowing; t denotes the year. The dependent variable $\bar{r}$ is constructed by averaging the local posted interest rate at geographic level g on year t for channel f, weighted by the local market share of the branch[13]. The bank branches' market share is defined by the branch level deposit over the total deposit of the local market. Similarly, we use the market share to construct the local HHI, total deposit, and number of branches at geographic level g on year t. Table 21 collects the regression results.

The table shows that HHI significantly impacts the interest rate: a high concentrated area has a higher interest rate for all finical products. However, the effect on different products is different: credit card borrowing is the most sensitive, while personal bank loan is less affected by the changes in the market concentration. Because different channels respond differently to the local financing market structure, investigating young firms' financing behavior needs to consider the local financing market variations.

8.2 Influence from increasing financing cost

In fact, the concentration changes in a general equilibrium model will have multiple ways affecting the firm's financing supply-side variation. However, this model abstracts away the strategic interaction between firm owners and lenders and focuses on the impact of increasing interest rates. In the model, the parameter ξ is assumed to represent the local financing market concentration level. To link the market concentration to the interest rate cost for each channel, I rewrite the interest rate function:

$$r(r_f, \xi, \bar{h}_f, k_t) = r_f^{1+\xi \frac{\varphi_f b_{f,t+1}}{k_t}},$$

where φ_f denotes the channel f's relative sensitivity to the financing environment changes[14], and $\frac{b_{f,t+1}}{k_t}$ capture the fact that firm's financing cost is increasing as this new debt coverage ratio goes

[13] If two or more branches in the local area belong to the same financial hold group, I treat them as the single big branch in that local area.

[14] Based on the coefficients of empirical analysis, φ_b is normalized to 1, φ_p is set to 0.9 and φ_c is set to 1.4.

down.

By setting ξ to a wide range set, we can test how the increasing financing cost affects young firms' debt-taking behavior and their future growth paths. As shown in the empirical analysis, the local bank industry concentration increment leads to the increasing firm's borrowing cost, particularly for no secured and high-risk channels, for example, credit card borrowing. As a result, small-size firms suffer more during the consolidation process. To quantitatively study the effect of the local financing environment, I conduct a series of exercises by setting ξ into $\{0, 0.25, 0.5, 0.75, 1\}$, where $\xi = 0$ is the benchmark.

Low-type firms First, let us see how low-type firms' growth dynamics and financing choices respond to the concentrated financing market. Figure 20 plots the the changes in the average capital accumulation for debt firms. We see that as the cost of financing increases, debt firms display different capital accumulation patterns. Under a moderate concentrated environment, i.e., $\xi = 0.25$, debt firm can have a higher asset level compared with the baseline model (figure 20b). This outcome can be explained in table 22. Under this scenario, debt firms above the median of the capital size distribution use more business loans for financing, both in the extensive and intensive margin. The outstanding debt amount is reduced, which lowers firms' financing costs. The positive effect of the business loans on capital accumulation plus the reduced debt amount elevates firms long-run capital accumulation path

Second, debt firms suffer from a decreasing long-run growth path when the market is highly concentrated and financing cost is too high. In other words, debt firms become smaller and smaller. Such a pattern is mainly driven by firms at the bottom tile of the distribution. Under a high-cost environment, most debt firms turn to self-financing within three years of development, as shown in figure 22a. The remaining debt firms are flooded with small firms that rely on external financing for survival. Due to a lack of capital stock, these firms' revenue earning is low. The high financing cost not only eats up firms' retained profit but also makes firms too costly to borrow more money for expansion. As a result, small debt firms gradually sell their capital to reduce costs and debt burden and decline the long-run growth potential.

High-type firms Different from low-type firms, high-type firms display a consistent downward trending pattern on the capital level as shown in figure 21. Because many high-type firms rely on external financing to maintain their business activities, firms have to reduce their debt to avoid high financing costs, which withdraws their business activities. As we learned from the previous section, from debt firms to non-debt firms, a large fraction of high-type firms will experience a significant drop in capital size, even lower than non-debt firms' capital level.

Figure 22b reports the downward trend of the debt-taking ratio when the Initial revenue financing environment becomes increasingly concentrated. Unlike the rapid decline in the low-type group, high-type firms' debt-taking rate remains a relatively high level (40%) even in a highly concentrated market, i.e., $\xi = 0.75$. However, the average debt-taking amount still keeps the increasing trend when a high-type firm lives in a concentrated financing environment (figure 23b).

In short, an increasingly concentrated financing market reduces a firm's long-run growth potential. However, under a mild concentrated environment, it is also possible that the firm's size distribution can be shifted right. The shift direction is closely related to the debt-taking ratio and access to business loans for up-tile firms in the distribution.

9 Conclusion

The relationship between firm dynamics and financing support is a long-standing topic in the literature. Motivated by the role young firms played in the economy, this research critically investigates the relationship between young firms' financing choices and their future growth dynamics. Particularly, this paper also considers the firm's ex-ante heterogeneity. Moreover, regarding the increasing concentrated financing market, this research also seeks to understand how young firms react to the changes in the local financing environment.

By building a firm life cycle model with financing constraints, I investigate the mechanism between choices of different financing channels and their development strategy. Three main channels are considered in this research, including business loans, personal loans, and credit card borrowing. In this model, the firm's heterogeneity stems from the firm owners' characteristics, such as education level, working experience, and work hours. Hence, Firms can be grouped into low and high types. The model cost structure links the firms' financing decisions to the investment strategies. Firms make optimal investment and borrowing decisions by balancing the expansion for higher revenue and bearing the high cost and default risk.

With the simulated method of moments, I back out the firm's cost structure for both low-and high-type firms. From the estimated parameters, I find that firms will increase when they are small. Seeking external debt financing helps small firms survive the bad times. During good times, the extra profits are often used to pay off the outstanding debt first for low-type firms rather than expanding businesses. One of the main distinctions between low- and high-type firms is the use of the capital structure and the combination of different financing channels to help development.

I find that first, access to business loans will help high-type firms increase their long-run growth potential in the comparative statistics. Second, restricting a firm's access to credit card borrowing causes a sharp decline in the debt-taking ratio and a much slower growth rate for the firm cohort. Additionally, the increasing concentrated bank industry will cause the rapid increment of financing costs for young firms. However, large firms tend to switch to self-financing while small firms still rely on external debt for survival and have to bear the high-cost burden.

Regarding the growing literature on discussing the firm's ex-ante heterogeneity and the post-entry dynamics, this research fills the gap about the interactions between young firms' heterogeneity and financing choices. Helping young firms have more financing options will be more effective in alleviating firms' financing constraints than reducing the interest rate for a few hard-to-access channels.

Table 1: Firm Characteristics

Statistics are based on the Kauffman Firm Survey using the stratified sample weights.

	2004	**2007**	**2011**	**Total**
Business Legal Status				
Sole proprietorship	35.8	33.9	31.4	34.2
Limited liability corporation	30.5	30.5	32.9	31.0
Corporation	28.1	30.5	31.7	29.6
Partnership	5.5	5.0	3.7	4.9
Others	0.2	0.1	0.3	0.2
Intellectual Property				
Patent	11.6	14.0	14.4	12.9
Trademark	41.2	42.3	34.4	40.2
Copyright	47.2	43.7	51.2	46.8
High Tech Company				
Not High Tech	94.4	94.3	93.5	94.2
High Tech	5.6	5.7	6.5	5.8
Product/Service Offerings				
Product offered	13.7	12.0	12.6	12.9
Service offered	48.5	52.7	56.5	51.6
Business offers both	37.8	35.3	30.9	35.6
Consumer Location				
Nationwide		11.7	11.4	11.6
City/State		68.0	65.6	67.1
Neighborhoods/local		20.3	23.1	21.4
Employment Size				
0	59.1	44.3	47.4	51.9
1	13.9	14.0	12.7	13.7
2	9.0	10.4	9.1	9.5
3	4.6	7.5	5.6	5.8
4-5	5.8	8.5	8.9	7.3
6-10	3.9	7.5	8.5	6.0
11-19	2.1	3.8	3.8	3.0
20+	1.5	3.8	4.2	2.8

Source: KFS

Table 2: Firm Owner's Demographic Characteristics

Statistics are based on the Kauffman Firm Survey using the stratified sample weights.

	2004	**2007**	**2011**	**Total**
Primary owner gender				
female	31.5	29.8	30.4	30.7
male	68.5	70.2	69.6	69.3
Primary owner race				
White	82.5	83.5	84.2	83.1
Black	8.7	8.3	8.1	8.5
Asian	3.7	4.1	4.4	3.9
other	5.1	4.1	3.4	4.4
Primary owner age				
18-24	1.5	0.4	0.6	1.0
25-34	17.4	9.8	12.3	13.9
35-44	33.6	29.4	33.3	32.2
45-54	28.6	32.2	31.1	30.3
55+	18.9	28.2	22.7	22.6
Firm ownership percentage				
<25%	4.4	3.6	3.4	4.0
26%-50%	25.7	24.7	22.5	24.7
51%-75%	4.6	6.1	4.9	5.1
76%-100%	65.3	65.6	69.2	66.2
Primary owner education				
HS grad or less	14.4	12.3	10.6	13.0
Tech/trade/voc. Deg.	6.7	7.0	6.5	6.8
Some coll., no deg.	22.7	22.1	22.2	22.4
Associate's	8.3	8.6	8.5	8.5
Bachelor's	24.0	24.5	25.1	24.4
Some grad, no deg.	5.8	6.1	6.4	6.0
Master's degree	12.9	13.2	13.4	13.1
Professional/doctorate	5.1	6.1	7.2	5.9
Industry Exp. (Yrs.)				
0	9.5	7.7	6.1	8.3
1-2	13.7	12.8	11.3	12.9
3-5	16.0	14.3	11.2	14.5
6-9	10.1	9.9	11.2	10.3
10-14	14.0	15.7	15.7	14.9
15-19	11.4	11.4	13.7	11.9
20-24	9.5	10.3	12.3	10.3
25-29	7.1	8.2	7.8	7.6
30+	8.6	9.6	10.8	9.4
Primary owner hours worked				
<20	18.0	19.8	20.8	19.1
20-35	19.5	18.4	20.6	19.4
36-45	14.5	15.8	18.4	15.7
46-55	15.2	18.9	17.5	16.8
>56	32.8	27.2	22.6	29.0

Source: KFS

Table 3: Low-type firms' activities and financing behavior

This table reports the simple cross-sectional statistics of firm's economic activities and financing behavior under low-type firms.Statistics are based on the Kauffman Firm Survey years 20042011 using the stratified sample weights.

	2004	2005	2006	2007	2008	2009	2010	2011
Employment	0.87	1.7	1.6	1.41	1.599	1.39	1.42	1.95
Revenue/Assets	1.588	2.09	2.66	3.16	2.45	3.27	2.62	3.6
Has debt	0.423	0.436	0.389	0.385	0.421	0.374	0.368	0.281
Has business loan	0.154	0.208	0.218	0.244	0.159	0.221	0.214	0.136
Has personal loan	0.379	0.283	0.25	0.256	0.209	0.201	0.174	0.16
Business loan ratio	0.096	0.137	0.157	0.16	0.098	0.146	0.134	0.1
Personal loan ratio	0.297	0.22	0.193	0.169	0.15	0.104	0.129	0.099

Table 4: High-type firms' activities and financing behavior

This table reports the simple cross-sectional statistics of firm's economic activities and financing behavior under high-type firms. Statistics are based on the Kauffman Firm Survey years 20042011 using the stratified sample weights.

	2004	2005	2006	2007	2008	2009	2010	2011
Employment	4.53	6.07	6.49	7.25	6.25	7.09	8.64	9.8
Revenue/Assets	2.78	3.57	4.32	3.87	4.57	4.79	6	4.82
Has debt	0.589	0.526	0.565	0.579	0.6	0.54	0.477	0.521
Has business loan	0.289	0.37	0.325	0.421	0.469	0.444	0.453	0.404
Has personal loan	0.439	0.344	0.297	0.301	0.257	0.245	0.266	0.175
Business loan ratio	0.195	0.249	0.226	0.3	0.328	0.308	0.344	0.3
Personal loan ratio	0.331	0.236	0.196	0.165	0.149	0.116	0.096	0.117

Table 5: Accumulated assets growth rate

This table reports the impact of access to different financing channels at initial stage on future accumulated assets growth. Estimates are based on the Kauffman Firm Survey years 20042011 using the stratified sample weights. The standard errors are within parentheses. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

	1 year		2 years		3 years	
Credit shock	0.141	0.105	0.122	0.0312	0.207*	0.163
	(0.221)	(0.224)	(0.196)	(0.174)	(0.089)	(0.0919)
Has business loan		0.738*		3.19**		1.7*
		(0.352)		(0.926)		(0.836)
Has personal loan		0.331		0.82		0.39
		(0.545)		(0.901)		(0.573)
Has credit card		0.801		0.0375		-0.21
		(0.483)		(0.362)		(0.257)
	-0.766***	-0.799	-1.13***	-1.235***	-0.89***	-0.868***
	(0.0865)	(0.080)	(0.254)	(0.224)	(0.133)	(0.119)
Initial employment	0.337	0.261	0.807	0.563	-0.054	-0.216
	(0.238)	(0.242)	(0.456)	(0.48)	(0.66)	(0.692)
Initial revenue	-0.042	-0.047	0.0115	0.0392	-0.116	-0.098
	(0.034)	(0.0432)	(0.04)	(0.0343)	(0.0753)	(0.081)
Home based	-1.25**	-1.21	-1.45*	-1.334	-0.702***	-0.624
	(0.422)	(0.439)	(0.067)	(0.718)	(0.161)	(0.174)
Controls	YES	YES	YES	YES	YES	YES
N	2601	2594	2231	2224	1936	1931

Table 6: Accumulated employment growth rate

This table reports the impact of access to different financing channels at initial stage on future accumulated employment growth. Estimates are based on the Kauffman Firm Survey years 20042011 using the stratified sample weights. The standard errors are within parentheses. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

	1 year		2 years		3 years	
Credit shock	0.0122	0.0134	-0.0108	-0.0128	-0.028	-0.031
	(0.0294)	(0.029)	(0.0553)	(0.0531)	(0.037)	(0.033)
Has business loan		-0.021		-0.1703**		-0.134
		(0.069)		(0.0637)		(0.088)
Has personal loan		0.0144		0.192***		0.1496*
		(0.0784)		(0.044)		(0.068)
Has credit card		-0.0626		-0.037	In the	-0.126**
		(0.050)		(0.0484)		(0.0615)
Initial assets	-0.033	0.0343	0.0171	0.0168	0.0225	0.024
	(0.193)	(0.0177)	(0.0147)	(0.0128)	(0.0202)	(0.0187)
	-0.67***	-0.665***	-0.764***	-0.745***	-0.82***	-0.808***
	(0.0453)	(0.046)	(0.0878)	(0.090)	(0.0794)	(0.0796)
Initial revenue	-0.003	-0.0036	-0.0072	-0.0076	0.0234	0.0255
	(0.014)	(0.013)	(0.0157)	(0.0156)	(0.0192)	(0.0181)
Home based	-0.363***	-0.364***	-0.494***	-0.494***	-0.464***	-0.466***
	(0.079)	(0.082)	(0.0534)	(0.052)	(0.055)	(0.053)
Controls	YES	YES	YES	YES	YES	YES
N	3117	3108	2671	2663	2351	2343

Table 7: Accumulated revenue growth rate

This table reports the impact of access to different financing channels at initial stage on future accumulated employment growth.Estimates are based on the Kauffman Firm Survey years 20042011 using the stratified sample weights. The standard errors are within parentheses. (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

	1 year		2 years		3 years	
Credit shock	0.848	0.81	0.719	0.665	1.24	1.143*
	(0.552)	(0.533	(0.74)	(0.742)	(0.53)	(0.521)
Has business loan		-0.558		0.06		2.22*
		(0.871)		(1.68)		(1.13)
Has personal loan		1.45		0.306		-1.173
		(1.053)		(0.422)		(1.23)
Has credit card		2.70**		1.99*		1.079
		(0.975)		(0.967)		(1.08)
Initial assets	0.568**	0.48**	-0.026	-0.085	0.674**	0.646***
	(0.197)	(0.193)	(0.502)	(0.511)	(0.197)	(0.206)
Initial employment	2.10**	2.17**	2.91***	2.99***	3.387**	3.27**
	(0.74)	(0.78)	(0.745)	(0.822)	(1.02)	(1.09)
	-3.376***	-3.36***	-3.81***	3.79***	-5.246***	-5.25***
	(0.415)	(0.43)	(0.709)	(0.710)	(0.56)	(0.571)
Home based	-3.326**	-3.145**	-4.64***	-4.51***	-6.81**	-6.66**
	(1.125)	(1.10)	(0.751)	(0.734)	(2.38)	(2.4)
Controls	YES	YES	YES	YES	YES	YES
N	2078	2073	1783	1778	1550	1546

Table 8: Summary of predetermined parameters

Parameter	Description	Value	Source
β	dicount rate	0.95	-
δ	capital deprecaitate rate	0.15	DeAngelo et al. (2011)
κ	capital resale discount	0.0954	Khan and Thomas (2013)
r_b	average business bank loan	1.046	Rate-watch
r_p	average personal bank loan	1.087	Rate-watch
r_c	average credit card borrowing	1.176	Rate-watch
τ	tax rate	0.8	Belo et al. (2019)

Table 9: Estimation for revenue function

Calculation are based on firms from the Kauffman Firm Survey data using the whole sample period, 2004-2011. Estimation is done with indirect inference. The target moments are the estimated coefficients from OLS and Tobit:$\{\overline{\phi}_1, \overline{\phi}_2, \overline{\phi}_3, \overline{\phi}_4\}$. The estimation proceed by matching the moments from a simulated panel of firms to the corresponding moments from the data. The first panel reports the simulated and estimated moments. The second panel reports the estimated cost structure paramters, with standard errors in paretheses. ϕ_0 is the constant term. ϕ_1 is the marginal return for capital stock. ϕ_2 is the second order for the marginal return for capital stock. ϕ_3 is the effect of firm's type. And ϕ_4 is the influence from the credit record.

A. Moments

	Data		Simulation	
	OLS	Tobit	OLS	Tobit
$\overline{\phi}_1$	0.685	1.540	0.631	1.512
$\overline{\phi}_2$	-0.032	-0.112	-0.034	-0.099
$\overline{\phi}_3$	0.903	1.684	1.045	1.378
$\overline{\phi}_4$	-0.196	-0.280	-0.202	-0.269

B. Parameter estimates

$\phi_0(const)$	$\phi_1(k)$	$\phi_2(k^2)$	$\phi_3(A)$	$\phi_4(\lambda)$
-0.9825	0.9936	-0.0556	1.4498	-0.2995
(0.1559)	(0.0246)	(0.0027)	(0.0605)	(0.0569)

Table 10: Estimation for borrowing limit of business loans

Calculation are based on firms from the Kauffman Firm Survey data using the whole sample period, 2004-2011. Estimation is done with indirect inference. The target moments are the estimated coefficients from OLS and Tobit:$\{\bar{\gamma}_1^b, \bar{\gamma}_2^b, \bar{\gamma}_3^b\}$. The estimation proceed by matching the moments from a simulated panel of firms to the corresponding moments from the data. The first panel reports the simulated and estimated moments. The second panel reports the estimated cost structure paramters, with standard errors in paretheses. γ_0^b is the constant term. γ_1^b is the collateral conversion ratio from the capital stock. γ_2^b is the effect of firm's type. γ_3^b is the influence from the credit record.

A.Moments

	Data		Simulation	
	OLS	Tobit	OLS	Tobit
$\bar{\gamma}_1^b$	0.183	0.609	0.188	0.590
$\bar{\gamma}_2^b$	0.231	0.887	0.203	0.937
$\bar{\gamma}_3^b$	-0.355	-1.042	-0.365	-0.978

B. Parameter estimates

$\gamma_0^b(const)$	$\gamma_1^b(k)$	$\gamma_2^b(A)$	$\gamma_3^b(\lambda)$
-2.9064	0.6272	1.1019	-0.9783
(1.5923)	(0.1507)	(0.2905)	(0.2308)

Table 11: Estimation for borrowing limit of personal loans

Calculation are based on firms from the Kauffman Firm Survey data using the whole sample period, 2004-2011. Estimation is done with indirect inference. The target moments are the estimated coefficients from OLS and Tobit:$\{\overline{\gamma}_1^p, \overline{\gamma}_2^p, \overline{\gamma}_3^p, \overline{\gamma}_4^p\}$. The estimation proceed by matching the moments from a simulated panel of firms to the corresponding moments from the data. The first panel reports the simulated and estimated moments. The second panel reports the estimated cost structure paramters, with standard errors in paretheses. γ_0^p is the constant term. γ_1^p is the extra granted line of credit if the firm also has business loans.γ_2^p is the collateral conversion ratio from the capital stock. γ_3^p is the substitutional pattern between business loans and personal loans. γ_4^p is the effect of firm's type.

A.Moments

	Data		Simulation	
	OLS	Tobit	OLS	Tobit
$\overline{\gamma}_1^p$	0.430	2.090	0.434	2.046
$\overline{\gamma}_2^p$	0.190	0.579	0.195	0.601
$\overline{\gamma}_3^p$	-0.132	-0.429	-0.128	-0.427
$\overline{\gamma}_4^p$	-0.188	-0.675	-0.202	-0.624

B. Parameter estimates

$\gamma_0^p(const)$	$\gamma_1^p(1_{bus})$	$\gamma_2^p(k)$	$\gamma_3^p(1_{bus} \cdot k)$	$\gamma_4^p(A)$
-2.0018	1.2745	0.6477	-0.1794	-0.7036
(0.6187)	(0.7691)	(0.0622)	(0.1046)	(0.2418)

Table 12: Estimation for low-type firms' cost structure

Calculation are based on the subsample of low-type firms from the Kauffman Firm Survey data. The high and type firms are defined by the group clustering method in appendix A. The sample period is 2004-2011. Estimation is done with SMM, which chooses structural model parameters (cost structure) by matching the moments from a simulated panel of firms to the corresponding moments from the data. The first panel reports the simulated and estimated moments. The second panel reports the estimated cost structure paramters, with standard errors in paretheses. c_{k1}^{+} and c_{k1}^{-} are the fixed components of the capital adjustment cost for upward and downward,respectively. c_{k2} is the convex component of the capital adjustment cost. c_{b0} is the fixed cost paid by debt firms in each time. c_{b1} is the leverage discount. Depending the sign of the coefficient, it measures the potential cost/benefit of leverage to improve the firm's management. c_{b2} is the convex component of the debt adjustment cost.

A.Moments

	Data	Simulation
Downward capital adjustment with debt	-0.192	-0.198
Upward capital adjustment with debt	0.231	0.242
Downward capital adjustment without debt	-0.221	-0.228
Upward capital adjustment without debt	0.261	0.258
Downward debt adjust ratio	-0.263	-0.234
Upward debt adjust ratio with debt	0.260	0.272
Debt taking ratio	0.342	0.342
Capital level for leveraged firms	4.608	4.738
Capital level for zero-leveraged firms	3.469	3.474
Debt level for leveraged firms	2.971	2.542

B. Parameter estimates

c_{k1}^{+}	c_{k1}^{-}	c_{k2}	c_{b0}	c_{b1}	c_{b2}
0.13501	0.13542	0.7541	0.155	-0.0746	0.5245
(0.11)	(0.048712)	(0.36469)	(0.0746)	(0.04239)	(0.3225)

Table 13: Estimation for high-type firms' cost structure

Calculation are based on the subsample of high-type firms from the Kauffman Firm Survey data. The high and type firms are defined by the group clustering method in appendix A. The sample period is 2004-2011. Estimation is done with SMM, which chooses structural model parameters (cost structure) by matching the moments from a simulated panel of firms to the corresponding moments from the data. The first panel reports the simulated and estimated moments. The second panel reports the estimated cost structure paramters, with standard errors in paretheses. c^+_{k1} and c^-_{k1} are the fixed components of the capital adjustment cost for upward and downward,respectively. c_{k2} is the convex component of the capital adjustment cost. c_{b0} is the fixed cost paid by debt firms in each time. c_{b1} is the leverage discount. Depending the sign of the coefficient, it measures the potential cost/benefit of leverage to improve the firm's management. c_{b2} is the convex component of the debt adjustment cost.

A.Moments

Match moments	Data	Simulation
Downward capital adjustment with debt	-0.125	-0.131
Upward capital adjustment with debt	0.163	0.233
Downward capital adjustment without debt	-0.141	-0.136
Upward capital adjustment without debt	0.153	0.208
Downward debt adjust ratio	-0.220	-0.206
Upward debt adjust ratio with debt	0.246	0.205
Debt taking ratio	0.536	0.501
Capital level for leveraged firms	6.570	6.749
Capital level for zero-leveraged firms	5.930	5.908
Debt level for leveraged firms	4.400	4.022

B. Parameter estimates

c^+_{k1}	c^-_{k1}	c_{k2}	c_{b0}	c_{b1}	c_{b2}
0.020495	0.040205	0.70528	0.12501	-0.21046	0.345
(0.01061)	(0.0161)	(0.3232)	(0.0752)	(0.09509)	(0.20659)

Table 14: Debt taking behavior and capital level across firm size distribution

The second column is the average value at the firm's entry stage. Starting in the third columns, the decomposition of firm's capital size distribution is based on firm's 7 years of development. Panel A reports the high-type firms and panel B reports the low-type firms. For this decompostion, I run the simulation 50 times and take the mean value of the interested varaibles.

A High-type firms

	First year	6 years later						
Percentile range	0-100	0-100	0-10	0-25	0-50	50-100	75-100	90-100
Has debt	0.548	0.506	0.610	0.442	0.388	0.645	0.797	0.992
Has business loans	0.303	0.510	0.224	0.262	0.325	0.641	0.691	0.735
capital for debt firms	5.804	6.777	2.439	3.408	4.497	8.386	8.914	9.425
capital for no-debt firms	5.078	5.908	2.750	3.934	5.021	7.703	8.389	9.208
outstanding debt	4.130	3.937	1.811	2.421	3.043	4.568	4.664	4.596

B Low-type firms

	First year	6 years later						
Percentile range	0-100	0-100	0-10	0-25	0-50	50-100	75-100	90-100
Has debt	0.4395	0.3199	0.1936	0.1578	0.1880	0.4573	0.8523	0.9984
Has business loans	0.1045	0.2062	0.0718	0.0984	0.1328	0.2377	0.2485	0.3120
capital for debt firms	4.2252	4.8184	1.8433	2.450	3.0903	5.5588	5.7201	6.2718
capital for no-debt firms	3.3654	3.4871	1.8210	2.535	2.9483	4.3273	4.8025	6.2688
outstanding debt	2.9643	2.5535	1.2189	1.5952	1.8735	2.8448	2.9313	3.2160

Table 15: Impact of fixed capital cost on low-type firms' financing decisions and capital level

This table is about low-type firms. Four key variables are summarized in this table: the average debt-taking ratio in panel A; the average business-loan-taking ratio in panel B; the average capital level for firms with debt in panel C; the average captial level for firm without debt in panel D. The columns diplay the changes of firm's fixed cost for upward capital adjustment, $c_{k1}+$, which variabes from 0 to 0.04 across the columns of the table equally. The rows in each panel is the firm's fixed cost for downward capital adjustment, which variaes from 0.06 to 0.18 across down the rows equally.

fixed cost of downward adjustment	fixed cost of upward adjustment low				high
A. Has debt					
low	0.3386	0.0972	0.0617	0.0558	0.0555
	0.3373	0.3384	0.3333	0.3281	0.3272
	0.3283	0.3299	0.3305	0.3301	0.3248
	0.3194	0.316	0.3152	0.3149	0.3158
high	0.3209	0.2974	0.3003	0.3022	0.3018
B. Has business loans					
low	0.4704	0.2894	0.2332	0.2061	0.1922
	0.2797	0.2597	0.2627	0.2536	0.2523
	0.2422	0.2272	0.2234	0.2259	0.2324
	0.2033	0.1895	0.1894	0.1971	0.1852
high	0.1697	0.1476	0.1365	0.1353	0.136
C. Capital level for debt firms					
low	6.6592	5.8359	4.9425	4.6358	4.5037
	6.0116	5.7704	5.7295	5.6356	5.5965
	5.5047	5.2845	5.1298	5.0714	5.093
	4.8934	4.6579	4.5878	4.633	4.5659
high	4.4891	4.2198	4.0945	4.0723	4.0484
D. Capital level for non-debt firms					
low	5.0498	5.0426	5.001	4.9705	4.8768
	4.3368	4.248	4.1571	4.0447	3.9745
	3.7578	3.6869	3.6626	3.5936	3.5544
	3.4295	3.374	3.3161	3.2556	3.266
high	3.2329	3.1898	3.1924	3.22	3.1198

Table 16: Impact of fixed capital cost on high-type firms' financing decisions and capital level

This table is about high-type firms. Four key variables are summarized in this table: the average debt taking ratio in panel A; the average business-loan-taking ratio in panel B; the average capital level for firms with debt in panel C; the average captial level for firm without debt in panel D. The columns diplay the changes of firm's fixed cost for upward capital adjustment, $c_{k1}+$, which variabes from 0 to 0.04 across the columns of the table equally. The rows in each panel is the firm's fixed cost for downward capital adjustment, which variaes from 0.06 to 0.18 across down the rows equally.

fixed cost of downward adjustment	fixed cost of upward adjustment				
	low				high
A. Has debt					
low	0.4086	0.4158	0.4515	0.4645	0.4734
	0.4662	0.4691	0.4698	0.4706	0.4717
	0.8104	0.8148	0.8502	0.8591	0.8606
	0.9296	0.9178	0.9274	0.9304	0.9326
high	0.9624	0.9573	0.9654	0.9686	0.9675
B. Has business loans					
low	0.4892	0.4784	0.4826	0.4746	0.4626
	0.5023	0.4862	0.4735	0.4582	0.4447
	0.5181	0.5017	0.4924	0.4755	0.4595
	0.485	0.4677	0.4565	0.4405	0.4258
high	0.4591	0.4358	0.4216	0.4102	0.3945
C. Capital level for debt firms					
low	6.5745	6.5135	6.6127	6.5347	6.4536
	6.7711	6.588	6.4487	6.3133	6.1878
	6.9421	6.7555	6.6423	6.4711	6.3098
	6.4917	6.296	6.171	6.0207	5.842
high	6.1361	5.9052	5.7577	5.5951	5.4454
D. Capital level for non-debt firms					
low	6.9318	6.8326	6.7834	6.5789	6.3079
	6.2892	6.1362	6.1195	5.9318	5.7994
	4.7397	4.5469	4.3189	4.2763	4.1887
	3.6326	3.5988	3.4157	3.3681	3.3255
high	2.5755	2.6492	2.4971	2.3567	2.2757

Table 17: Impact of convex capital cost on low-type firms' financing decisions and capital level

This table is about low-type firms. Four key variables are summarized in this table: the average debt taking ratio in panel A; the average business-loan-taking ratio in panel B; the average capital level for firms with debt in panel C; the average captial level for firm without debt in panel D. The columns diplay the changes of firm's fixed cost for upward capital adjustment, $c_{k1}+$, which variabes from 0 to 0.04 across the columns of the table equally. The rows in each panel is the firm's convex cost for capital adjustment, which variaes from 0.5 to 0.9 across down the rows equally.

convex cost of adjustment	fixed cost of upward adjustment				
	low				high
A. Has debt					
low	0.3214	0.3197	0.3197	0.3182	0.319
	0.3194	0.3183	0.3181	0.3178	0.318
	0.318	0.3179	0.3176	0.3175	0.3186
	0.3172	0.3179	0.3179	0.3184	0.3132
high	0.3177	0.3185	0.3181	0.312	0.3037
B. Has business loans					
low	0.2477	0.2234	0.215	0.2208	0.2203
	0.2398	0.216	0.2166	0.215	0.2169
	0.2287	0.2097	0.2069	0.2128	0.2113
	0.2212	0.2045	0.204	0.2092	0.2048
high	0.2133	0.1989	0.2034	0.2083	0.1984
C. Capital level for debt firms					
low	5.4717	5.0476	4.9	4.918	4.881
	5.3504	4.9745	4.8614	4.8463	4.8581
	5.2328	4.9089	4.8257	4.8363	4.8206
	5.1372	4.8641	4.7801	4.8118	4.7789
high	5.0323	4.8064	4.7734	4.8073	4.7614
D. Capital level for non-debt firms					
low	3.7492	3.6579	3.6521	3.57	3.5493
	3.7055	3.6034	3.617	3.5419	3.5203
	3.6428	3.542	3.5079	3.4928	3.4836
	3.5652	3.523	3.4607	3.4359	3.4526
high	3.5445	3.4528	3.4408	3.4088	3.4025

Table 18: Impact of convex capital cost on high-type firms' financing decisions and capital level

This table is about high-type firms. Four key variables are summarized in this table: the average debt taking ratio in panel A; the average business-loan-taking ratio in panel B; the average capital level for firms with debt in panel C; the average captial level for firm without debt in panel D. The columns diplay the changes of firm's fixed cost for upward capital adjustment, $c_{k1}+$, which variabes from 0 to 0.04 across the columns of the table equally. The rows in each panel is the firm's convex cost for capital adjustment, which variaes from 0.5 to 0.9 across down the rows equally.

convex cost of adjustment	fixed cost of upward adjustment				
	low				high
A. Has debt					
low	0.4809	0.5425	0.737	0.7773	0.7763
	0.4897	0.5826	0.7367	0.7714	0.755
	0.507	0.6082	0.7354	0.7565	0.7442
	0.5264	0.64	0.7313	0.7437	0.7374
high	0.5369	0.6618	0.7303	0.7284	0.7225
B. Has business loans					
low	0.52	0.5147	0.526	0.5099	0.491
	0.5118	0.515	0.5175	0.5007	0.4854
	0.5054	0.5089	0.5082	0.4932	0.4763
	0.4998	0.5053	0.4992	0.486	0.4714
high	0.488	0.4992	0.4904	0.4785	0.4643
C. Capital level for debt firms					
low	6.9516	6.9232	7.0366	6.8585	6.6818
	6.8568	6.9027	6.9239	6.7682	6.6074
	6.78	6.8284	6.8244	6.6799	6.509
	6.7473	6.7874	6.7308	6.58	6.441
high	6.6479	6.7254	6.6431	6.4878	6.357
D. Capital level for non-debt firms					
low	6.1523	5.8447	5.1011	4.9092	4.8489
	6.0274	5.5942	5.0272	4.8576	4.865
	5.9197	5.4804	4.9443	4.8507	4.82
	5.7703	5.2746	4.8919	4.8284	4.7758
high	5.6689	5.0995	4.879	4.8356	4.7781

Table 19: Distributional effects of limited credit card channel on low-type firms' financing choices

	6 years later				
Percentile range	0-100	0-25	0-50	50-100	75-100
	credit limits = 2.5				
Has debt	0.323	0.164	0.172	0.467	0.853
Has business loans	0.203	0.073	0.367	0.242	0.259
	credit limits = 2				
Has debt	0.331	0.192	0.215	0.456	0.849
Has business loans	0.186	0.065	0.080	0.239	0.255
	credit limits = 1.5				
Has debt	0.325	0.256	0.249	0.410	0.626
Has business loans	0.157	0.052	0.071	0.217	0.240
	credit limits = 1.25				
Has debt	0.152	0.146	0.118	0.196	0.394
Has business loans	0.169	0.056	0.069	0.246	0.260
	credit limits = 1				
Has debt	0.023	0.072	0.045	0.002	0.003
Has business loans	0.062	0.045	0.049	0.387	0.643

Table 20: Distributional effects of limited credit card channel on high-type firms' financing choices

	6 years later				
Percentile range	0-100	0-25	0-50	50-100	75-100
	credit limits = 4				
Has debt	0.503	0.441	0.415	0.597	0.768
Has business loans	0.497	0.258	0.303	0.639	0.718
	credit limits = 3				
Has debt	0.495	0.495	0.461	0.532	0.651
Has business loans	0.462	0.219	0.281	0.638	0.717
	credit limits = 2				
Has debt	0.498	0.622	0.543	0.448	0.493
Has business loans	0.395	0.166	0.233	0.615	0.707
	credit limits = 1				
Has debt	0.513	0.788	0.663	0.352	0.356
Has business loans	0.301	0.113	0.173	0.561	0.670

Table 21: Impact of local market concentration on financing channels interest cost

The table reports the interest rate reactions of each channel to the local bank industry concentration. The market concentration HHI is calculated by the total deposit of each financial institutions over the total deposit in that area. The interest rate is the average interest rate across branches in the corresponding local market. The geographic level is at the county level. To make it comparable with the KFS data, the time period ranges from 2004 to 2011. For each channel, I run two regression, the first one is simple OLS while the second one controls for the fixed effect of the geographic locations.

	bus loan interest rate		Pers loan interest rate		Credit card interest rate	
	(1)	(2)	(1)	(2)	(1)	(2)
HHI	1.349***	0.5723***	1.395***	0.355***	1.902***	0.477**
	(0.051)	(0.11)	(0.043)	(0.088)	(0.099)	(0.214)
# of branches	0.3278***	0.4404**	0.47***	0.45**	1.09***	1.39***
	(0.074)	(0.183)	(0.01)	(0.146)	(0.14)	(0.453)
local deposit	-0.3113***	-0.659***	-0.2005***	-0.717***	-0.701***	-1.01***
	(0.05)	(0.117)	(0.042)	(0.092)	(0.095)	(0.233)
Cons	-5.294	5.081	-7.45	7.65	-6.63	7.32
Fixed effects	No	Yes	No	Yes	No	Yes
N	6693	6509	12373	12220	3754	3615

Table 22: Low-type firms reaction to moderate increment financing cost

Ages	2	3	4	5	6	7
	Capital level of debt firms at 50-100 percentile					
$\xi = 0$	5.035	5.269	5.474	5.512	5.542	5.559
$\xi = 0.25$	4.976	5.246	5.427	5.499	5.555	5.578
	Debt taking ratio at 50-100 percentile					
$\xi = 0$	0.559	0.519	0.508	0.490	0.474	0.454
$\xi = 0.25$	0.556	0.504	0.508	0.485	0.464	0.445
	Has business loans at 50-100 percentile					
$\xi = 0$	0.102	0.143	0.135	0.138	0.137	0.134
$\xi = 0.25$	0.109	0.156	0.158	0.155	0.157	0.155
	Oustanding debt at 50-100 percentile					
$\xi = 0$	2.576	2.658	2.744	2.781	2.814	2.845
$\xi = 0.25$	2.390	2.385	2.444	2.492	2.536	2.567

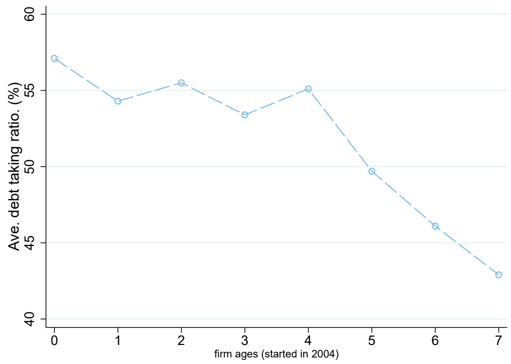


Figure 1: Young firm debt taking and exit ratio trend

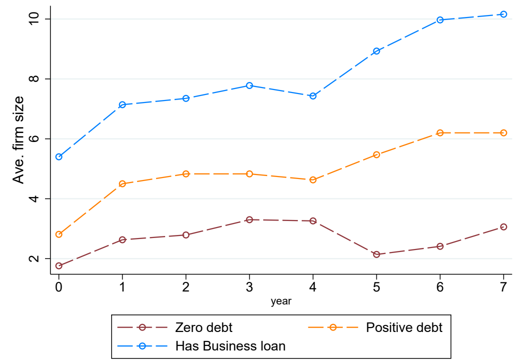


Figure 2: Firm size and debt taking behavior

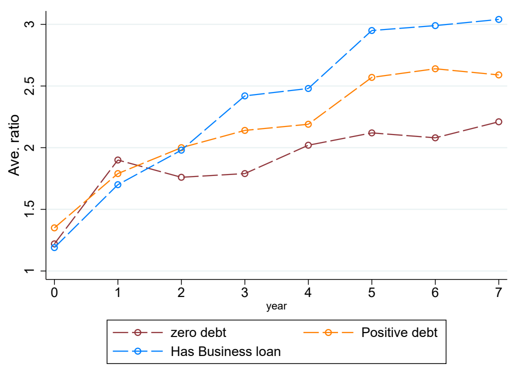


Figure 3: Firm revenue returns and debt taking behavior

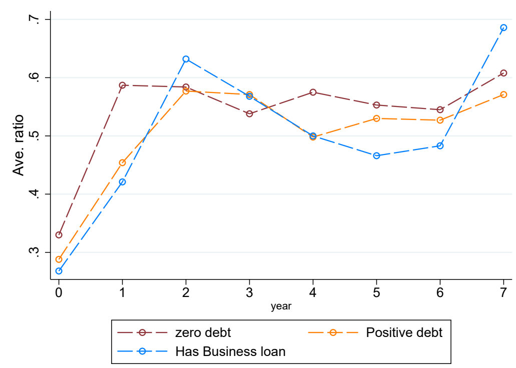


Figure 4: Firm profit returns and debt taking behavior

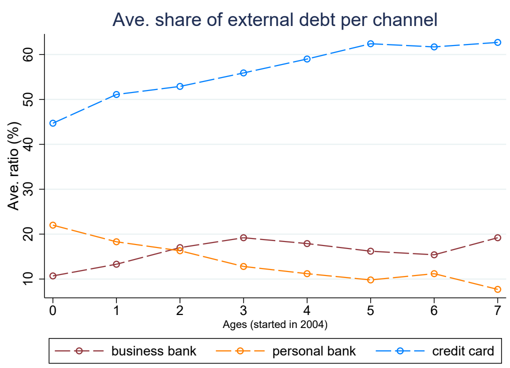


Figure 5: Average share of each channel's borrowing amount

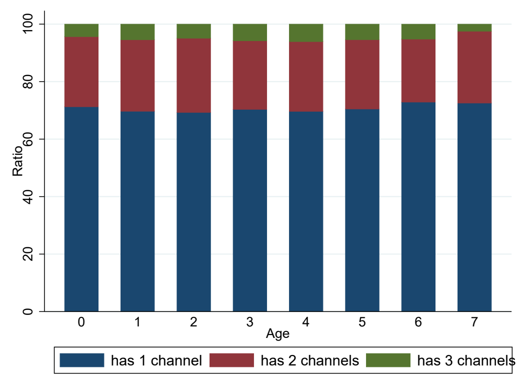


Figure 6: Average ratio of number of bank loan channels that firms utilize

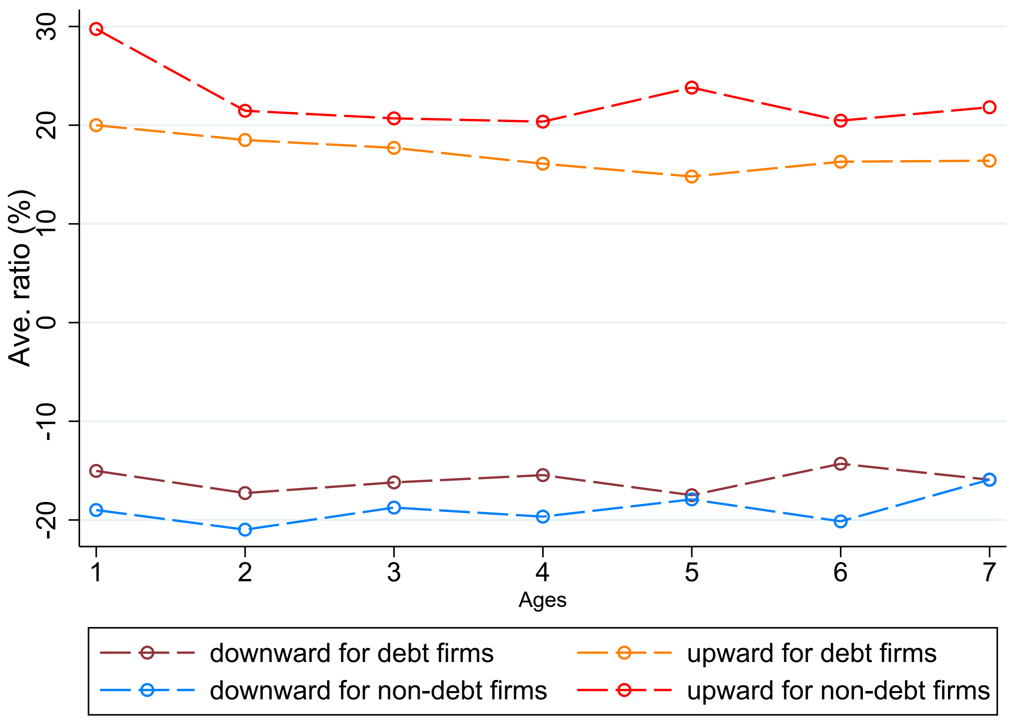


Figure 7: Average ratio of capital adjustment

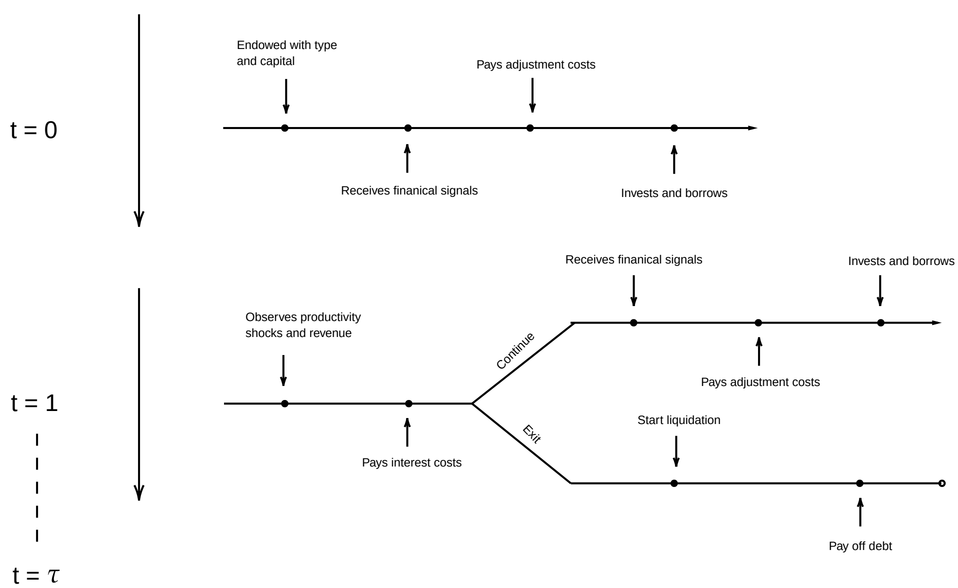


Figure 8: Model timeline

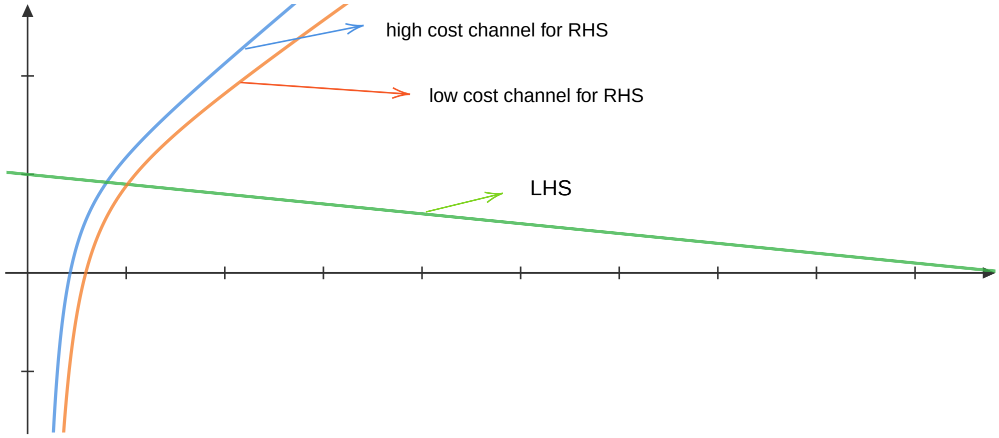


Figure 9: Simple comparison of low cost channel and high cost channel optimal choices

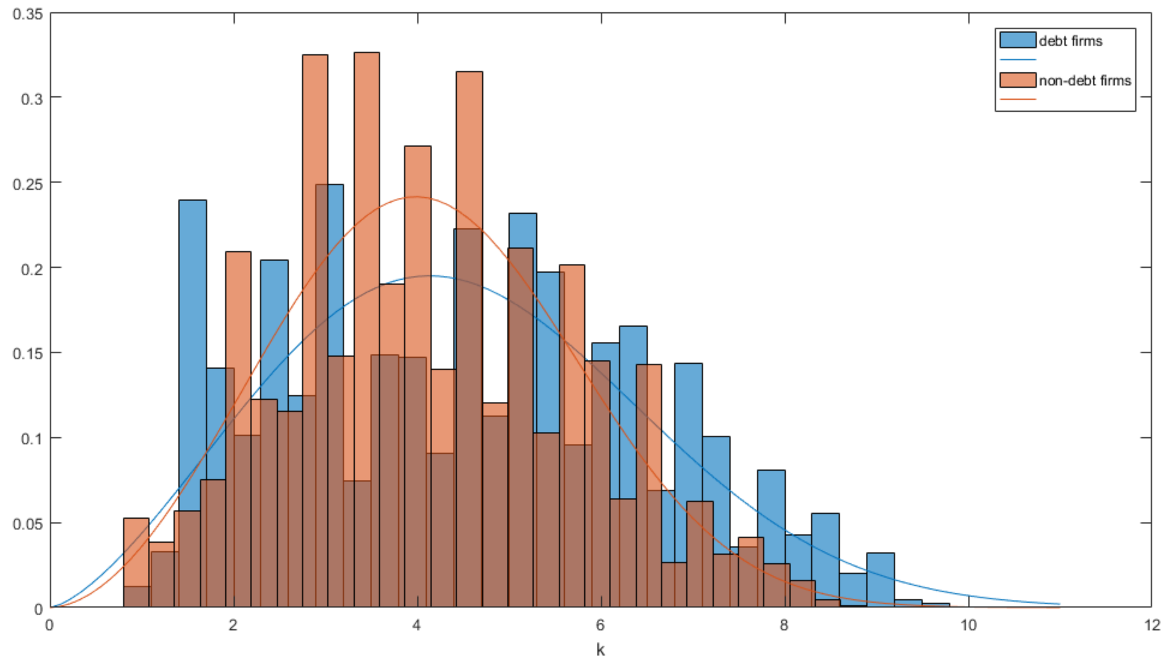


Figure 10: Low-type firm's long-run capital size distribution

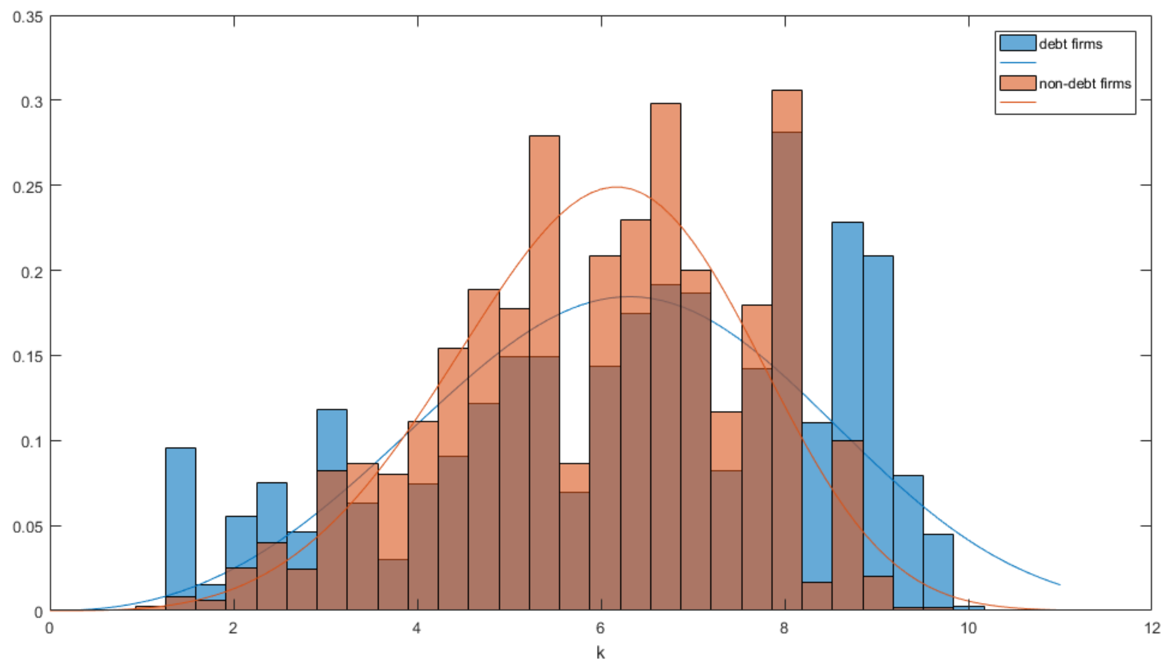
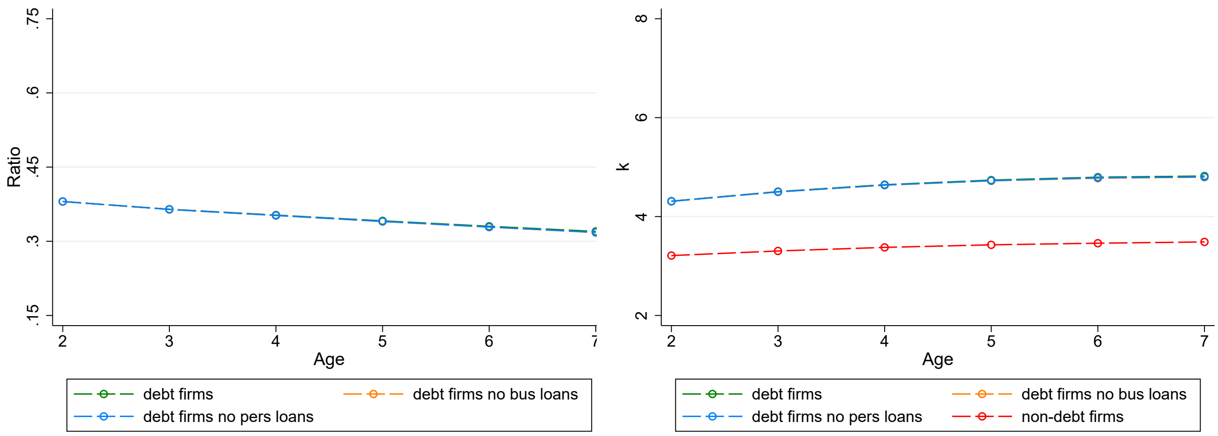


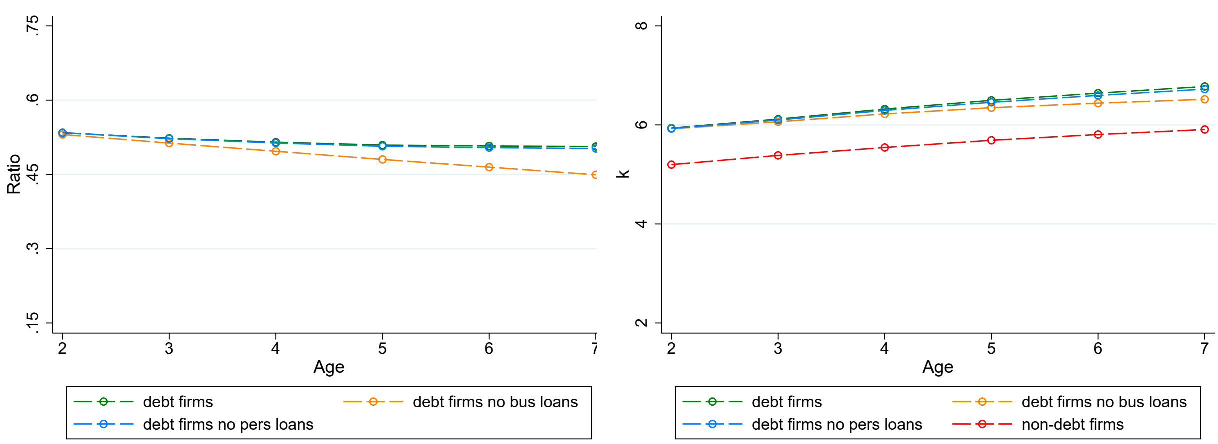
Figure 11: High-type firm's long-run capital size distribution



(a) Ave. debt taking ratio

(b) Ave. capital level

Figure 12: Impact of access to bank loans on low-type firms' long-run performance



(a) Ave. debt taking ratio

(b) Ave. capital level

Figure 13: Impact of access to bank loans on high-type firms' long-run performance

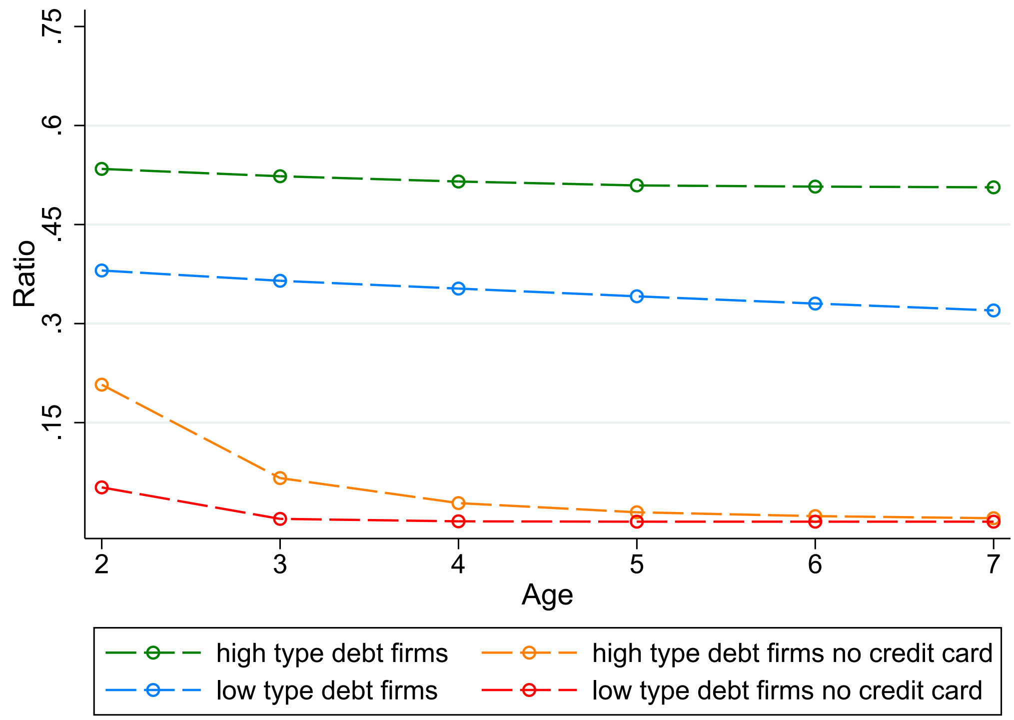
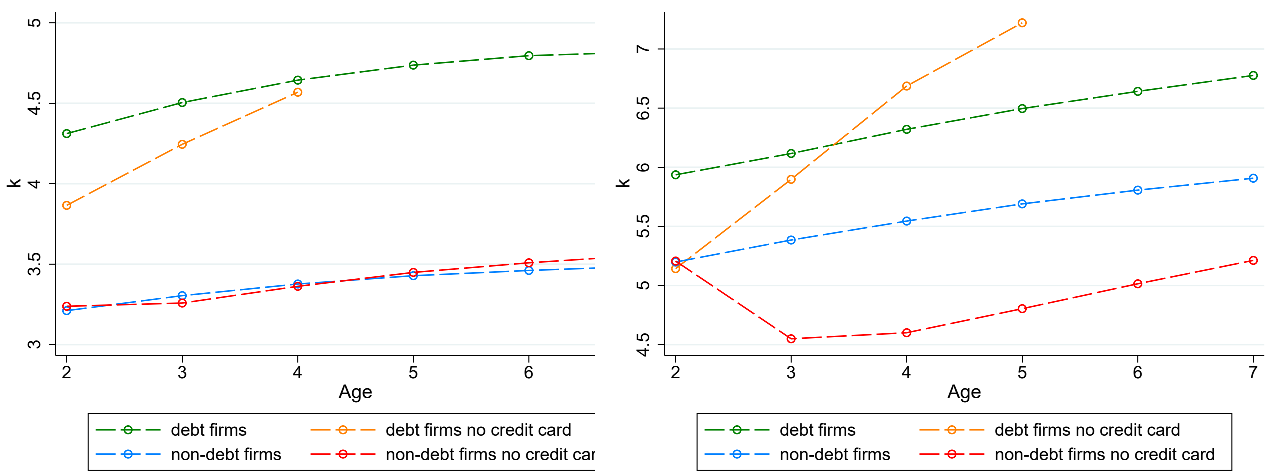


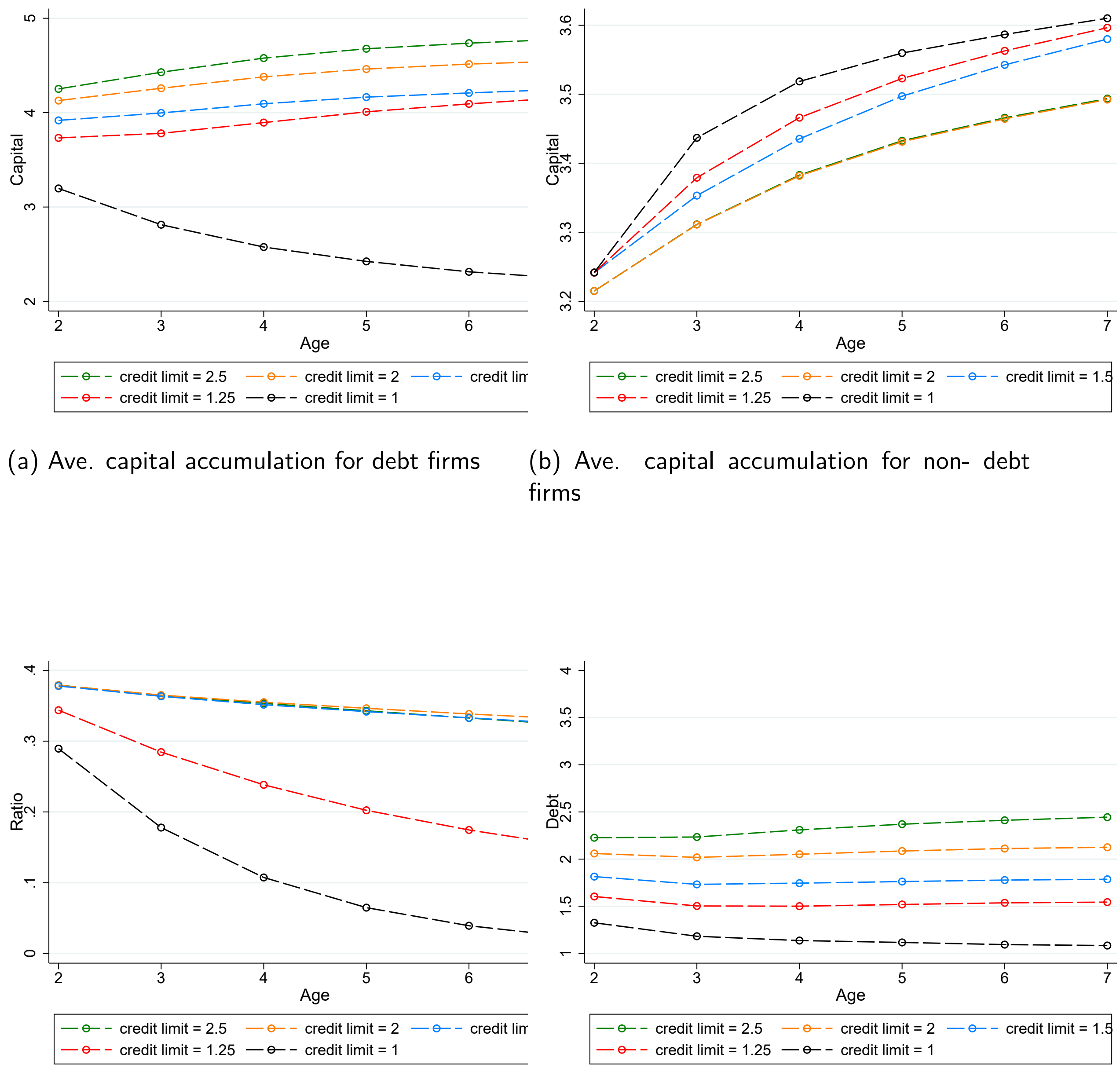
Figure 14: Impact of access to credit card on financing decisions



(a) Low-type

(b) High-type

Figure 15: Impact of access to credit card capital accumulation



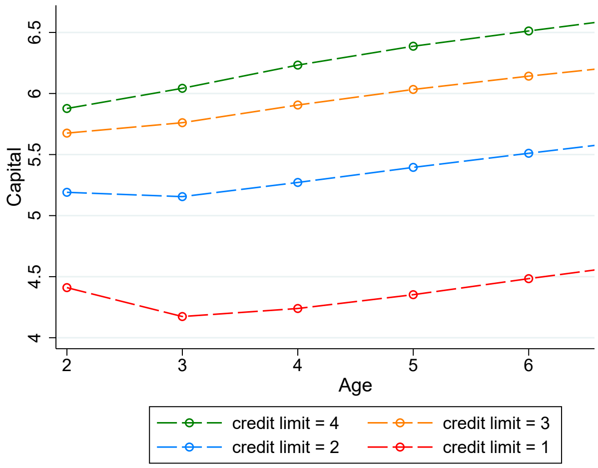
(a) Ave. capital accumulation for debt firms

(b) Ave. capital accumulation for non- debt firms

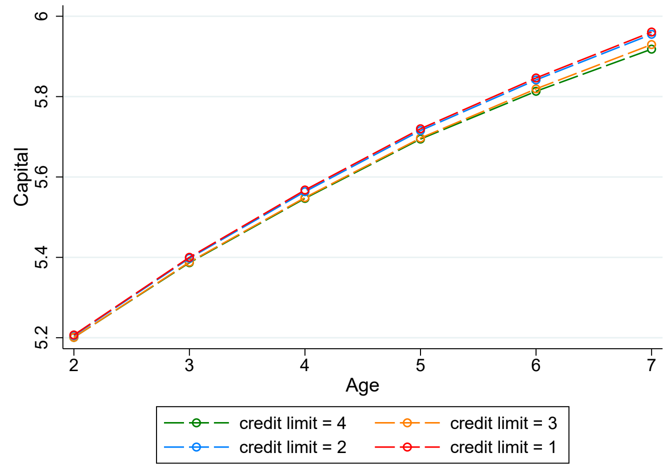
(c) Ave. debt taking ratio

(d) Ave. debt amount for debt firms

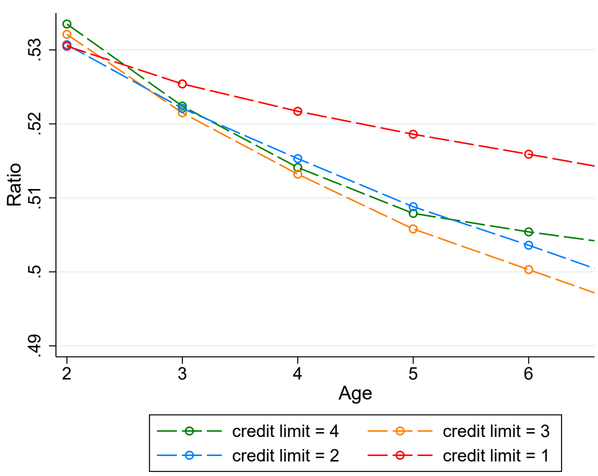
Figure 16: Borrowing limit in credit card borrowing for low-type firms



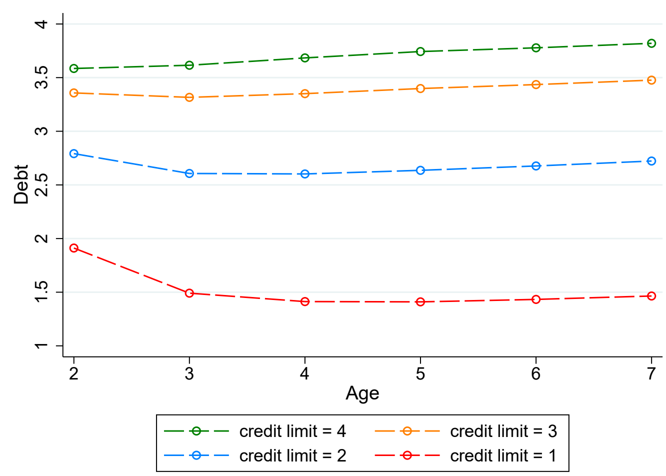
(a) Ave. capital accumulation for debt firms



(b) Ave. capital accumulation for non- debt firms

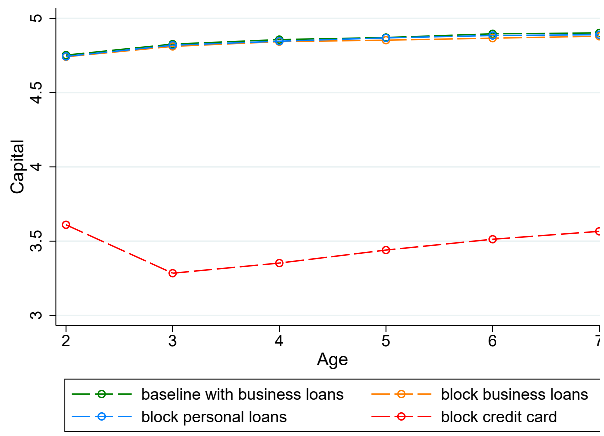


(c) Ave. debt taking ratio

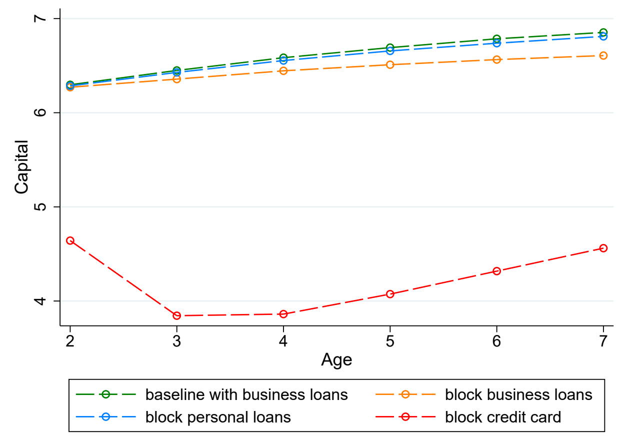


(d) Ave. debt amount for debt firms

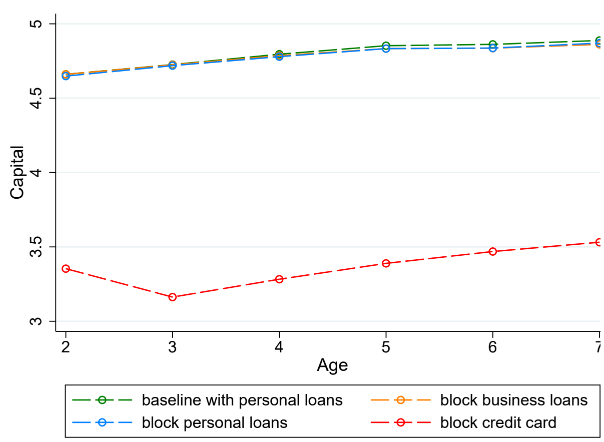
Figure 17: Borrowing limit in credit card borrowing for high-type firms



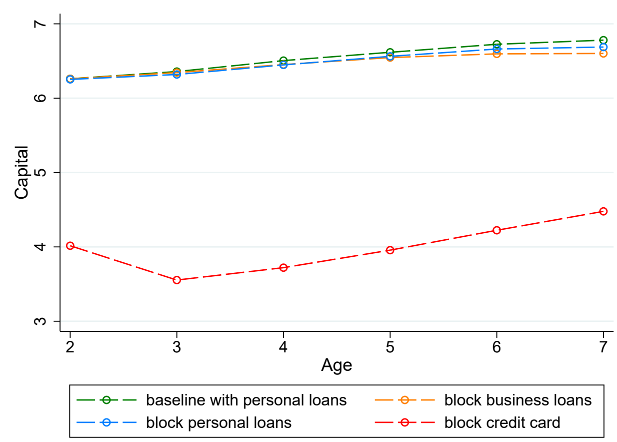
(a) Business loan channel from low-type firms



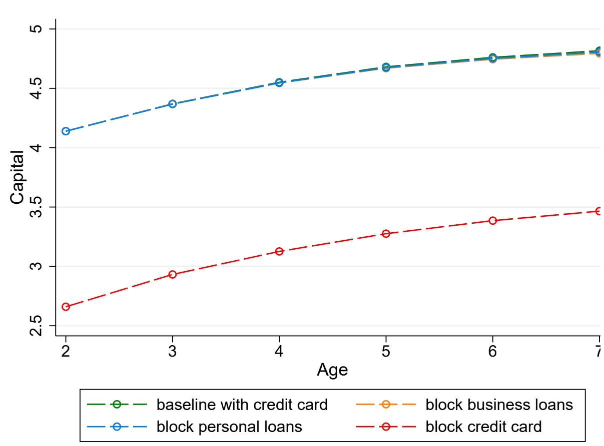
(b) Business loan channel from high-type firms



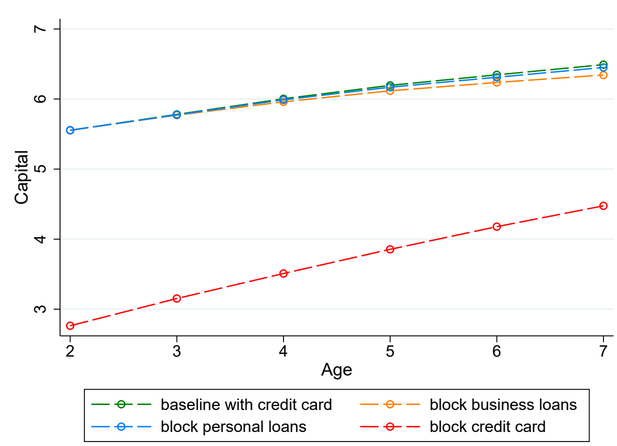
(c) Personal loan channel from low-type firms



(d) Personal loan channel from high-type firms



(e) Credit card borrowing from low-type firms



(f) Credit card borrowing from high-type firms

Figure 18: Each channel's direct effect on firms' long-run capital accumulation

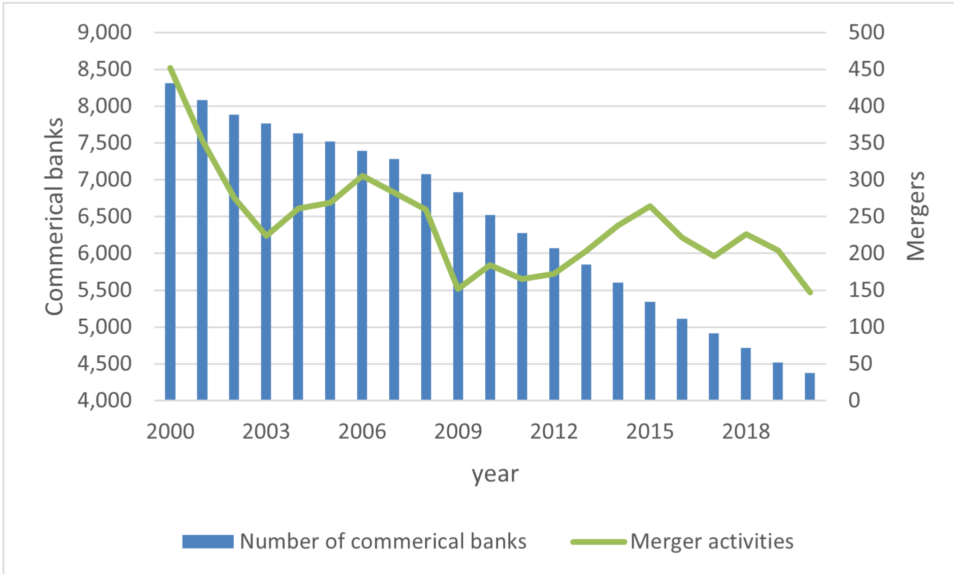
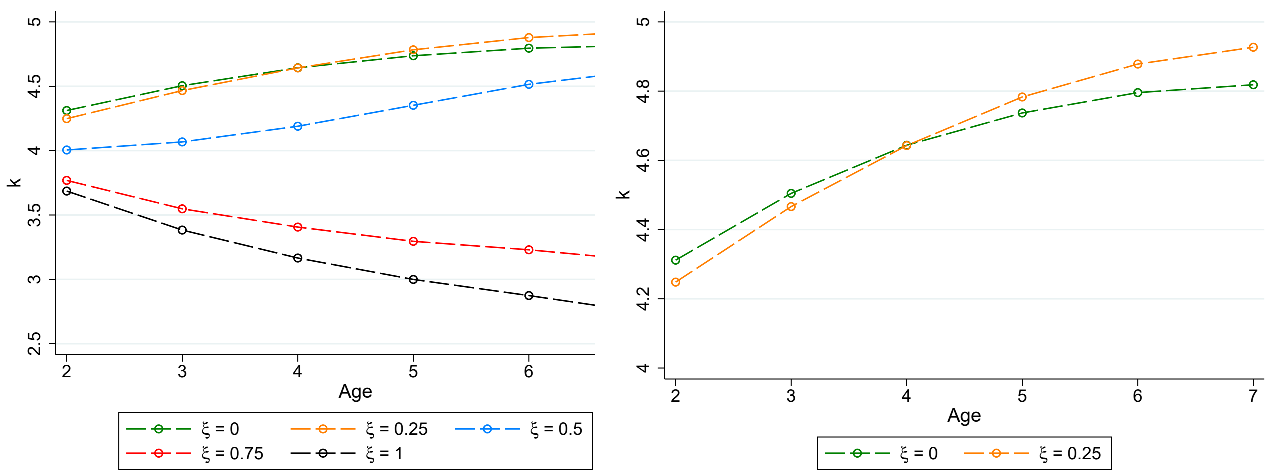


Figure 19: Merger trend of commerical banks



(a) different concentrated environment

(b) moderate concentrated environment

Figure 20: Impact of increasing financing cost on low-type firms' average capital accumulation

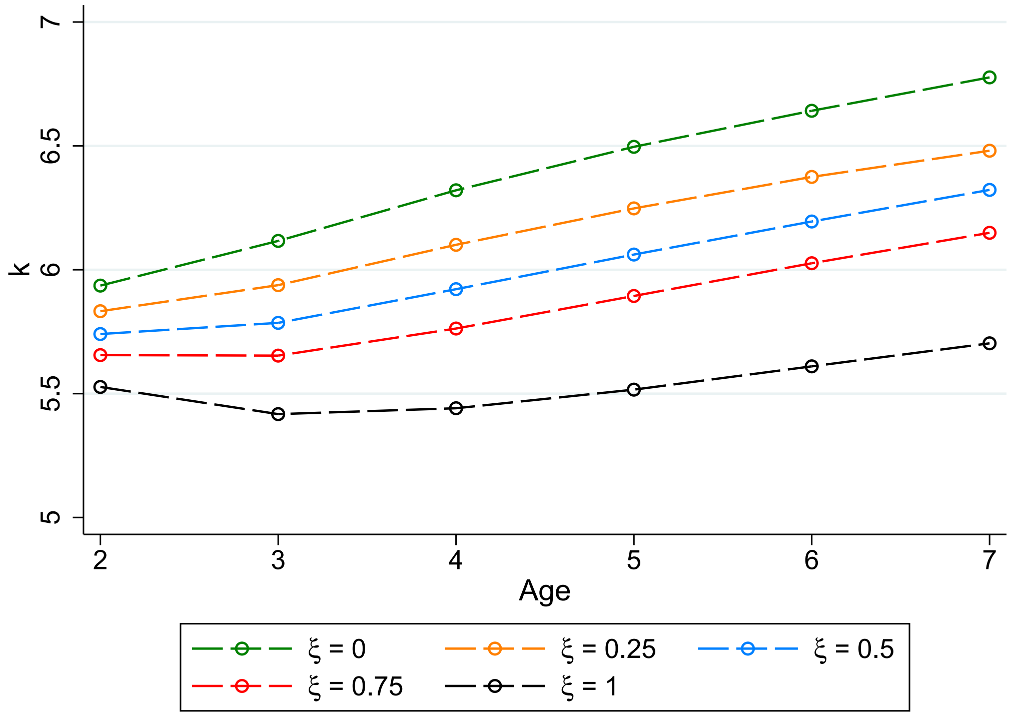
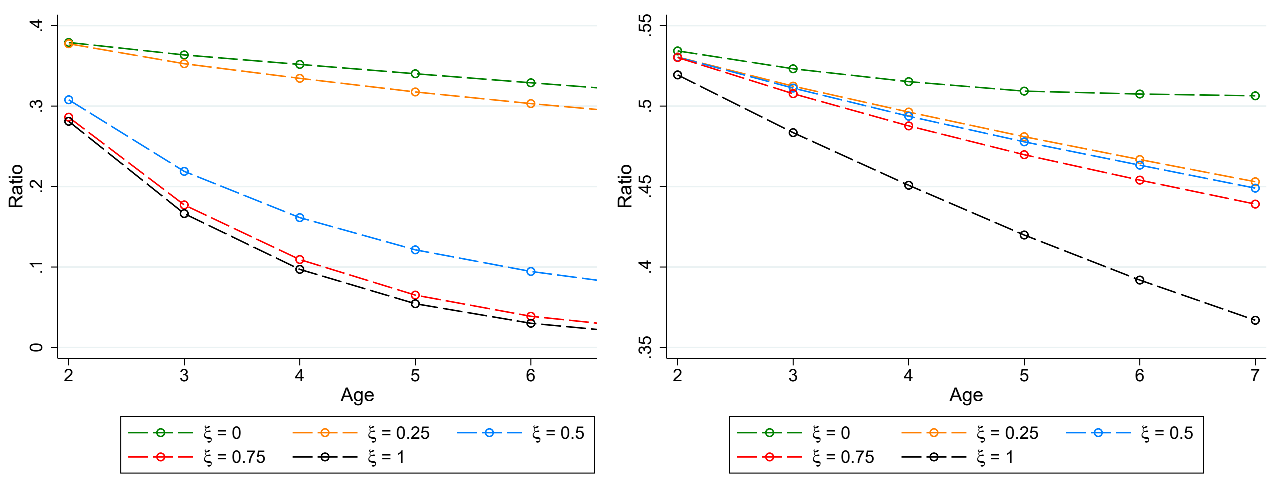
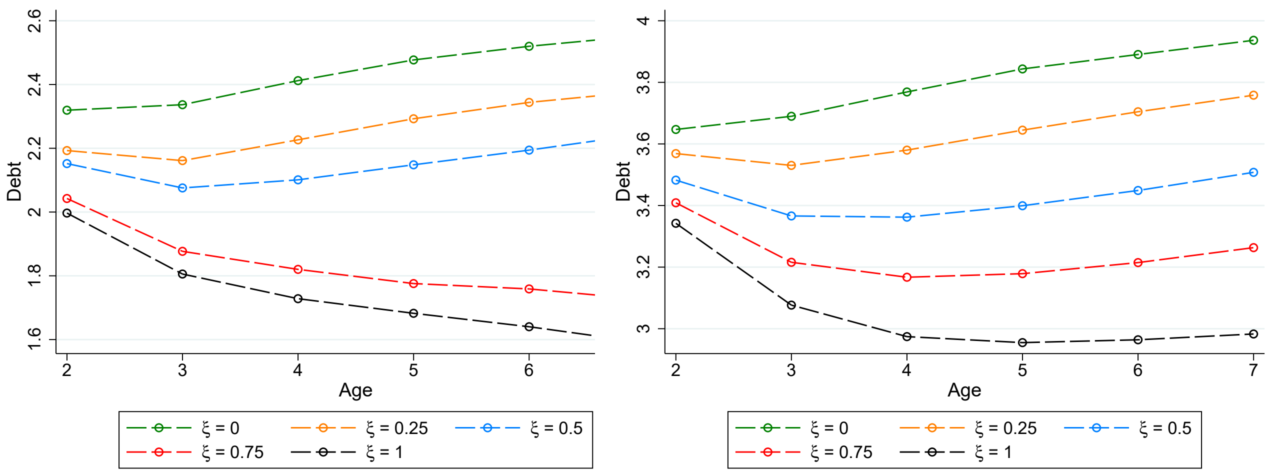


Figure 21: Impact of increasing financing cost on high-type firms' average capital accumulation



(a) Low-type (b) High-type

Figure 22: Impact of increasing financing cost on firms' debt taking ratio



(a) Low-type (b) High-type

Figure 23: Impact of increasing financing cost on firms' debt taking ratio

References

Albuquerque, R. and Hopenhayn, H. A. (2004). Optimal lending contracts and firm dynamics. *The Review of Economic Studies*, 71(2):285–315.

Arellano, C., Bai, Y., and Zhang, J. (2012). Firm dynamics and financial development. *Journal of Monetary Economics*, 59(6):533–549.

Belo, F., Lin, X., and Yang, F. (2019). External equity financing shocks, financial flows, and asset prices. *The Review of Financial Studies*, 32(9):3500–3543.

Berger, A. N. and Udell, G. F. (1998). The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle. *Journal of banking & finance*, 22(6-8):613–673.

Cabral, L. and Mata, J. (2003). On the evolution of the firm size distribution: Facts and theory. *American economic review*, 93(4):1075–1090.

Carvalho, V. M. and Grassi, B. (2019). Large firm dynamics and the business cycle. *American Economic Review*, 109(2011):1–58.

Clementi, G. L. and Hopenhayn, H. A. (2006). A theory of financing constraints and firm. *The Quarterly Journal of Economics*, pages 229–265.

Cole, R. A. and Sokolyk, T. (2018). Debt financing, survival, and growth of start-up firms. *Journal of Corporate Finance*, 50:609–625.

Cooper, R. W. and Haltiwanger, J. C. (2006). On the nature of capital adjustment costs. *The Review of Economic Studies*, 73(3):611–633.

Covas, F. and Den Haan, W. J. (2011). The cyclical behavior of debt and equity finance. *American Economic Review*, 101(2):877–99.

Crouzet, N. and Mehrotra, N. R. (2020). Small and large firms over the business cycle. *American Economic Review*, 110(11):3549–3601.

DeAngelo, H., DeAngelo, L., and Whited, T. M. (2011). Capital structure dynamics and transitory debt. *Journal of Financial Economics*, 99(2):235–261.

Decker, R., Haltiwanger, J., Jarmin, R., and Miranda, J. (2014). The role of entrepreneurship in us job creation and economic dynamism. *Journal of Economic Perspectives*, 28(3):3–24.

Evans, D. S. and Jovanovic, B. (1989). An estimated model of entrepreneurial choice under liquidity constraints. *Journal of political economy*, 97(4):808–827.

Greenstone, M., Mas, A., and Nguyen, H.-L. (2020). Do credit market shocks affect the real economy? quasi-experimental evidence from the great recession and" normal" economic times. *American Economic Journal: Economic Policy*, 12(1):200–225.

Haltiwanger, J., Jarmin, R. S., and Miranda, J. (2013). Who creates jobs? small versus large versus young. *Review of Economics and Statistics*, 95(2):347–361.

Hennessy, C. A. and Whited, T. M. (2005). Debt dynamics. *The journal of finance*, 60(3):1129–1165.

Hennessy, C. A. and Whited, T. M. (2007). How costly is external financing? evidence from a structural estimation. *The Journal of Finance*, 62(4):1705–1745.

Hopenhayn, H. and Rogerson, R. (1993). Job turnover and policy evaluation: A general equilibrium analysis. *Journal of political Economy*, 101(5):915–938.

Hopenhayn, H. A. (1992). Entry, exit, and firm dynamics in long run equilibrium. *Econometrica*, 60(5):1127.

Hurst, E. and Pugsley, B. W. (2012). What Do Small Businesses Do? *Brookings Papers on Economic Activity*, 2011(2):73–118.

Jermann, U. and Quadrini, V. (2012). Macroeconomic effects of financial shocks. *American Economic Review*, 102(1):238–71.

Khan, A. and Thomas, J. K. (2013). Credit shocks and aggregate fluctuations in an economy with production heterogeneity. *Journal of Political Economy*, 121(6):1055–1107.

Kocherlakota, N. et al. (2000). Creating business cycles through credit constraints. *Federal Reserve Bank of Minneapolis Quarterly Review*, 24(3):2–10.

Moreira, S. (2016). Firm dynamics, persistent effects of entry conditions, and business cycles. *Persistent Effects of Entry Conditions, and Business Cycles (October 1, 2016)*.

Quadrini, V. and Cooley, T. F. (2001). Financial markets and firm dynamics. *American Economic Review*, 91(5):1286–1310.

Robb, A. M. and Robinson, D. T. (2014). The capital structure decisions of new firms. *The Review of Financial Studies*, 27(1):153–179.

Sahlman, W. A. (1990). The structure and governance of venture-capital organizations. *Journal of financial economics*, 27(2):473–521.

Sedláček, P. and Sterk, V. (2017). The growth potential of startups over the business cycle. *American Economic Review*, 107(10):3182–3210.

Smirnyagin, V. (2019). Compositional nature of firm growth and aggregate fluctuations. *Available at SSRN 3514855*.

Stiglitz, J. E. and Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American economic review*, 71(3):393–410.

Strebulaev, I. A. and Yang, B. (2013). The mystery of zero-leverage firms. *Journal of Financial Economics*, 109(1):1–23.

Zarutskie, R. and Yang, T. (2015). How did young firms fare during the great recession? evidence from the kauffman firm survey. *Available at SSRN 2669566*.

Appendix

A. Firm's type classification procedure

To classify the whole data sample into high and low-type firms, I apply the propensity score matching method by utilizing the firm ex-ante characteristics and their initial status. The algorithm consists of two stages. In the first stage, I target selecting the predetermined groups. In the second stage, I use the matching method to assign candidate firms to either low or high-type repeatedly. The procedure is detailed as follows.

Step 1 The predetermined high-type firms are selected by setting all three metrics as the top 10% of the sample. Similarly, the predetermined low-type firms are picked under the bottom 10% of the data sample. The rest of the firms belongs to the candidate firms waiting to be selected into either high or low-type groups.

Step 2 To assign the type information to the candidate firms, I run two matching regressions separately.

1. I let the predetermined low-type firms as the treatment group and all candidate firms as the control groups. Then the firm's performance metrics and the firm and owner's characteristics are chosen to be the explanatory variables. By running probit/logit regression, we can obtain the propensity score for the low-type firm's situation.
2. Applying the same procedure, I can obtain the propensity score for the high-type firm's situation. Initial revenue
3. Now, each candidate firm has two propensity scores, and I can compare which score is higher. By the definition of the propensity score, a higher score means closer to the treatment group(low or high-type, respectively). To ensure the precision of the assignment, I drop the scores and the corresponding firms below 50% of the ranking.
4. After the new assignment, we get the new high and low-type subgroups and new subsets of candidate firms. We repeat the previous 1-3 steps until all the candidate firms are assigned to either high or low groups.

B. Model implications

Zero debt firms and their long-run growth paths From the data, we also notice that a large fraction of firms do not take any external debt—instead, they self-financing their businesses. Most of the zero-debt firms keep zero debt in the rest of their life cycles. When firms decide not to take debt, the investment decision becomes much simpler:

$$\psi^k + c_{k2}\left(\frac{k'}{k}\right) = \beta\mathbb{E}[\frac{d\pi}{dk'} + \frac{c_{k2}}{2}\left(\frac{k''}{k'}\right)^2], \tag{26}$$
$$\psi^k = 1 - \beta c_{k1} - (1-\delta)(\beta + \beta c_{k2} - c_{k2})$$

Compared with the firms with positive leverage, zero debt firms often have lower investments. The model can also explain this behavior. For a typical zero debt firm, taking debt means seeking an extra amount of "free lunch" at the current status with the cost of paying the interest rate and all kinds of debt adjustment costs in the future. Mathematically speaking, given current k, λ, and z, this happens only when the following inequality holds

$$\{-\bar{k}' + \beta\mathbb{E}V(\bar{k}', 0|A)\} < \max_{b',k'}\{b' - k' + \beta\mathbb{E}V(k', b'_R|A)\} \tag{27}$$
$$s.t. \tag{28}$$
$$b^R_{t+1} \leq \mathbb{E}[\pi_{t+1} + \kappa(1-\delta_k)k_{t+1} - c_{k1}k_{t+1} - c_{b1}\frac{b^R_{t+1}}{k_{t+1}}b^R_{t+1}]$$
$$\bar{k}' = \arg\min_{k'}\left\{(1-\tau)\left[\pi_t - k' + (1-\delta)k_t - C^k_t\right] + \tau\delta k_t + \beta\mathbb{E}V(k', 0|A)\right\} \tag{29}$$

We know that according to the monotonicity of value function on debt, i.e., $\frac{\partial V}{\partial b_R} < 0$, $\mathbb{E}_t V(k, 0, |A) > \mathbb{E}_t V(k, b_R, |A)\ \forall b_R > 0$. Then, the above equation (27) provides the threshold for us to see when zero debt firms decide to take debt. Given the exogenous shock z and credit record λ, by solving the equality of

$$\{-\bar{k}' + \beta\mathbb{E}V(\bar{k}', 0|A)\} = \min_{k'}\max_{b',k'}\{b' - k' + \beta\mathbb{E}V(k', b'_R|A)\},$$

we can get the minimum capital stock k^*_b that firms are indifferent of taking debt or not. This happens when the firm does not receive a good realization of revenue return, and the future profit can compensate for the financing cost. If the firm's optimal size is relatively small, the firm owner can wait a more extended period to grow without spending much more revenue to cover the unnecessary financing cost. Moreover, if the firm is already big enough, the owner also does not need to take debt. Because after a few period accumulations, the firm can get to their optimal size without taking any risks of financing distress. So if a firm does not take any debt at the initial stage, the firm will unlikely want to borrow in the future.