The Nature of Firm Financing and Growth*

Martin Aragoneses† Christopher Hansman‡ David Licher§
Ramana Nanda¶

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Abstract

Using confidential Census data on all UK incorporated firms between 2002 and 2024, we show that the age at which firms first access cash flow based long-term debt strongly predicts long run firm outcomes: firms that receive their first cash flow based debt at age 1 are 30% larger by age 20 than those first financed at age 5. These patterns contrast with asset-backed long-term debt, where the age at which it is first accessed is unrelated to long-run outcomes. To understand these patterns, we develop a tractable theory of firm life cycle dynamics with permanent heterogeneity and financing frictions – where access to finance is based on available collateral as well as on signals of *forward looking* firm value. The model highlights the importance of forward-looking financing in matching the predictability of cash-flow based financing observed in the data. It also highlights how frictions to the two forms of financing lead to differential selection and hence very different distributions of firms that survive and grow. In turn observed aggregate outcomes are different, as are potential policy responses. Simulating a richer, calibrated model shows that reducing frictions to forward looking financing in the UK would lead to more US-like unequal firm dynamics, including a larger number of "superstar firms".

Keywords: Credit Rationing; Unsecured Debt; Firm Dynamics; Learning

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†INSEAD. E-mail: martin.aragoneses@insead.edu
‡Emory University. E-mail: chris.hansman@emory.edu
§Imperial College London. E-mail: d.licher21@imperial.ac.uk
¶Imperial College London. E-mail: ramana.nanda@imperial.ac.uk

1 Introduction

How firms access external finance over their lifecycle is central to understanding firm growth, resource allocation, and aggregate productivity. A large literature (e.g. Kiyotaki & Moore (1997), Cooley & Quadrini (2001), Ottonello & Winberry (2020), Midrigan & Xu (2014)) emphasizes the role of financial frictions—particularly those tied to collateral constraints—in shaping firm dynamics (e.g. Hopenhayn (1992)). However, this view abstracts from a pervasive feature of real-world financial markets: a large share of financing is based not on collateral, but on investors' expectations of firms' future cash flows (Lian & Ma 2021). Whether—and how—the forward-looking nature of financing shapes firm dynamics remains largely unexplored.

In this paper, we combine unique longitudinal data on financing and growth for all incorporated UK firms with a new theoretical framework to explore how the nature of firm financing – particularly debt based on the expectation of future cash flows – relates to the nature of firm growth.[1] Motivated by (Lian & Ma 2021), we distinguish between two conceptually distinct forms of borrowing: asset-backed debt, which is secured against specific collateral (such as land or machinery) and cash-flow–based debt, which is largely unsecured and depends on lenders' expectations of future firm performance.

Building on this conceptual distinction, our paper proceeds in three steps. First, we show that the timing of first access to cash flow based long term debt (CF-LTD) is strongly predictive of subsequent real-outcomes. Firms that obtain CF-LTD early in life grow significantly larger. For example, those that receive their first CF-LTD at age 1 have 30% more employment and 40% more revenue at age 20 than those who first receive CF-LTD age 5. Strikingly, this predictability does not extend to asset-backed long-term debt (A-LTD). While collateralizable assets may expand borrowing capacity, the timing of first access to A-LTD has no predictive power for long-run employment,

[1]This is possible because all incorporated firms in the UK are required to file annual financial accounts with Companies House shortly after incorporation, generating near-universal panel data on firm financing from the earliest stages of firm activity. Matching these financial filings with panel data on firm employment from the UK Census provides a rare view into the evolution of financing and firm dynamics over the lifecycle for the universe of incorporated firms from 2002-2024.

revenue or assets.

The combination of these findings suggest that CF-LTD is fundamentally tied to firm growth and firm dynamics in a way that A-LTD is not. They also indicate the firms' ability to raise CF-LTD is based on something richer than just current cashflows. Instead lending decisions appear to incorporate informative, forward looking assessments of firms future performance and value. As a result, models that tie borrowing constraints only to collateral—or even to *current* cashflows—miss an important channel through which financing influences firm dynamics and aggregate outcomes.

In the second part of our paper, we develop a tractable theory of heterogeneous firms with life cycle dynamics and frictional financing to formalize these mechanisms. The model highlights the distinct patterns that emerge when financing is based on signals of forward-looking firm value relative to more standard collateral or current earnings based borrowing. Our central contribution is to highlight how the presence of permanent heterogeneity, which has received recent attention in the firm-dynamics literature, interacts with forward looking value-based financial constraints (a focus of recent macro-finance literature).

The *forward-looking* nature of financing is the key ingredient needed to rationalize the empirical relationship between CF-LTD and future performance. If forward looking financial frictions are so extreme that financing is related only to currently available collateral or earnings, selection will lead mature firms to appear as if they were ex-ante homogeneous—as in Hopenhayn (1992)— even if they are not. Alternatively, with less extreme frictions to forward looking financing, permanent differences in productivity– as in Melitz (2003)—become visible throughout the entire life cycle as firms converge towards different growth trajectories. As a consequence, forward looking financing is necessary to match the unequal growth trajectories that appear with cash-flow based financing (via a novel selection channel of future "superstar" firms). Alternatively, financing based on assets or current earnings generates the limited long-run inequality that we see among firms taking asset based debt.

The richness of our data allow us to evaluate several empirical implications of the

forward-looking financing constraints that feature in our model. Because the data provide a comprehensive view of financing from the earliest stages of firm activity, we document that CF-LTD is not only the dominant form of borrowing overall, but also particularly prevalent early in the lifecycle. This is precisely the stage at which firms' cash flows have not yet converged to more stable trajectories. In addition, we find that CF-LTD predicts more extreme growth trajectories in environments where financing constraints—and thus screening incentives—are likely to be tighter. This pattern is consistent with lenders selectively extending forward-looking credit to firms with the greatest long-run potential. Growth trajectories following CF-LTD are steeper when serial entrepreneurs enter new industries, where lender uncertainty is plausibly greater, versus when they remain in familiar sectors. The relationship is similarly stronger in more intangible-intensive industries. By contrast, the predictiveness of CF-LTD for subsequent growth weakens sharply during the COVID loan scheme, which reduced lenders' incentives to screen borrowers.

In the third and final part of our paper, we embed our frictional financing mechanisms into a structural firm dynamics model a la Sterk et al. (2021) that incorporates endogenous entry and exit as well as rich life cycle productivity dynamics. Counterfactuals with a preliminary calibration that matches the life cycle profiles of exit rates and firm size by age in UK data confirms the intuition built in the tractable model about patterns in the data. Early simulations show relaxing frictions that impair financiers from funding based on measures of value from future cash flows could lead to the UK economy having faster (US-like) firm life cycle dynamics that are more unequal in the long run.[2]

[2]While results for the richer model are thus far only qualitative in nature, we are exploring whether improvements in value-based financing could quantitatively help close the aggregate productivity gap with respect to the US, and whether they should be prioritized relative to more traditional efforts to relax asset-based or earning-based financial frictions.

Related Literature

Our research speaks to four primary strands of the literature: firm life cycle dynamics, the structural modeling of borrowing constraints in macro-finance, the informational role of screening in entrepreneurial and corporate finance, and the aggregate implications of credit-market misallocation.

A large body of work studies entry, exit, and the evolution of firms over the life cycle under selection and shocks. Foundational dynamic industry models show how selection shapes the size distribution and long-run outcomes when firms face idiosyncratic productivity risk and fixed or adjustment costs (Hopenhayn 1992, Ericson & Pakes 1995, Melitz 2003). Within macro, collateral or net-worth constraints have often been layered onto such frameworks to generate rich firm dynamics (Cooley & Quadrini 2001). More recent empirical work emphasizes that firm growth over the life cycle features a mix of persistence and randomness, with strong selection at early ages and persistent heterogeneity among survivors (Sterk et al. 2021). A parallel literature documents that young, high-potential firms disproportionately account for employment growth and skewness in firm outcomes (Haltiwanger et al. 2013, Decker et al. 2014). We build on Sterk et al. (2021) by studying more complex set of finanncing constraints that are both asset-based and value-based constraints. A key contribution of our paper is to highlight that permanent heterogeneity among firms has a very important interaction with financial constraints that are explicitly value based and forward looking. The combination of these factors allows for firms to be ex-ante heterogeneous as in Melitz (2003) while retaining ex-post shocks as in Hopenhayn (1992).

Indeed, in macro-finance, financing constraints are commonly modeled as either net-worth or earnings constraints that tie external finance to internal cash flow (Townsend 1979, Holmström & Tirole 1997), and collateral constraints that bind borrowing to pledgeable assets (Kiyotaki & Moore 1997, Cooley & Quadrini 2001). This tradition has delivered key insights into amplification, investment, and firm dynamics. Empirically, cash-flow sensitivity and asset tangibility are used to capture constraints (Hennessy & Whited 2007, Almeida & Campello 2007). Yet a growing corporate finance

literature distinguishes asset-based from cash-flow–based lending and shows the latter relies more on firm prospects and information production rather than collateral alone (Lian & Ma 2021). We add this tractable financing margin into a macro-finance framework—forward-looking, value-based lending governed by signals of expected future productivity—and we center this new lens on how young firms are financed from inception. Embedding this margin alongside collateral- and current earnings-based channels in a heterogeneous-firm life-cycle model yields two core results that line up with the data. First, selection under value-based lending is type-dependent: lenders screen on expected long-run potential rather than pledgeable assets, so initial heterogeneity persists into maturity and generates rank-predictability of growth that pure asset- or earnings-based constraints cannot match. Second, due to this type-dependent screening, the nature of selection in the face of frictions implies that surviving firms experience more extreme growth trajectories in environments where financing constraints—and thus screening incentives—are likely to be tighter.

A central theme in corporate and entrepreneurial finance is how lenders produce and act on information to extend credit absent hard collateral. Classic work on relationship lending and soft information shows how screening technologies and organizational design shape credit access for young and opaque firms (Petersen & Rajan 1994, Agarwal & Hauswald 2010). Survey evidence supports the idea that external debt is an important source of financing (Robb & Robinson 2014) and that the role of secured financing has decreased (Benmelech et al. 2024). We contribute new, economy-wide evidence that the timing of CF-LTD access is powerfully predictive of long-run real outcomes, consistent with lenders' forward-looking screening extracting information about firm potential that is not spanned by contemporaneous assets or cash flows. Our COVID-era evidence—where the UK Bounce Back Loan Scheme decoupled lending from screening—further supports the interpretation that prediction comes from screening itself: when screening is shut down, early CF-LTD ceases to forecast differential growth.

A large macro development and misallocation literature links financial frictions to dispersion in marginal products and to aggregate TFP losses (Hsieh & Klenow 2009,

Buera et al. 2011, Midrigan & Xu 2014, Gopinath et al. 2017). Much of this work models borrowing capacity via net worth or collateral, implicitly favoring tangible asset intensive firms. As production has shifted toward intangible intensive technologies with weak collateralizability, the gap between firm value and pledgeable assets has widened, lowering debt capacity and altering financing choices (Falato et al. 2022). We show that frictions in value based lending – rather than in collateralized lending per se – can generate sizable misallocation by preventing high potential, intangible intensive firms from obtaining early CF-LTD. Preliminary calibrated comparisons between the UK and US indicate that relaxing frictions to forward looking lending increases the prevalence of high growth superstar firms, steepens growth by age profiles, and raises aggregate productivity. These results connect with cross-industry evidence that financial development disproportionately benefits sectors more dependent on external finance (Rajan & Zingales 1998) and with firm level evidence that financing and legal environments matter differentially by firm size and opacity (Beck et al. 2005). Our framework highlights that in economies where intangible capital is increasingly central, improvements in screening technologies and in institutions that allow lenders to act on forward looking information can yield first order TFP gains by reallocating credit toward high potential young firms.

2 Data

We construct a novel panel dataset that merges firm-level real outcomes with comprehensive financing records for the universe of incorporated firms in the United Kingdom. This dataset is the result of a granular link between two primary administrative sources of firm-level data: the Business Structure Database (BSD) from the UK's Office for National Statistics (ONS) (Office for National Statistics 2025), which provides the official record of demographic, employment and turnover variables, and the Bureau van Dijk (Moody's) FAME dataset, which includes statutory financial filings from Companies House. The merge leverages a cross-walk provided by the ONS that maps the BSD's unique business identifiers (ENTREF) to the Companies House Company Registration

Numbers (CRN).

Our empirical setting offers a distinct comparative advantage over traditional administrative datasets, such as the US Longitudinal Business Database (LBD). In the UK, all incorporated entities are legally mandated to file statutory balance sheets within 21 months of incorporation, and these filings are accessible in the public domain. This institutional requirement allows us to observe the financial structure of firms at or near their inception. Consequently, we observe key financial data for the pre-entry or start-up phase – a period that typically remains a black box in other jurisdictions where firms only appear in administrative records after surpassing specific employment or turnover thresholds. Crucially, our data allows us to synchronize the first appearance of a firm in the BSD with its contemporaneous financial position.

Following the firm dynamics literature, we define Age 0 as the year a firm first enters the administrative records—specifically, the point at which it either hires its first employee or registers for VAT. This threshold ensures our lifecycle analysis focuses on economically active firms rather than the broader universe of inactive or shell incorporated entities. While administrative entry defines the start of a firm's economic life for our panel analysis, we also exploit precise incorporation dates for our quasi-experimental identification. Specifically, we utilize these granular dates to implement a Regression Discontinuity Design (RDD) centered on the March 2020 eligibility cutoff for the Covid-19 Bounce Back Loan Scheme (BBLS).

The granularity of the financial information allows for a more detailed decomposition of corporate liabilities than is typically possible with private-firm data. First, we observe standard balance sheet items, allowing us to disaggregate financing into equity, short-term debt, and long-term debt. Second, we exploit the UK's Register of Charges to identify the specific nature of debt contracts. We observe every secured loan via the charges or liens registered at Companies House, providing visibility into the lender's identity and the underlying collateral. We distinguish between fixed charges (tied to specific tangible assets) and floating charges (secured against non-specific assets and thus tied to future cash flows). We define LTD lending events as year-on-year increases

in LTD. We then categorize these events based on the underlying security: increases tied to a fixed charge are classified as asset-backed LTD (A-LTD), while increases tied to a floating charge or lending events on an unsecured basis are classified as cash flow-based LTD (CF-LTD).

Furthermore, we leverage the UK's public register of directors and shareholders to bridge the gap between firm-level outcomes and individual entrepreneurial characteristics. The director register provides identifying information for all directors and managers – including full names and birthdates – which enables the longitudinal tracking of individuals across different firms and over time. We map the shareholder register to the list of directors to identify the type of equity holders (e.g., owner-managers vs. outside investors). This allows for the construction of a comprehensive managerial and ownership history, enabling us to investigate the role of prior entrepreneurial experience.

To comply with data privacy regulations and ONS security protocols, this identification process was conducted in a secure environment prior to the final merge. All individual identifiers were pseudonymized; specifically, names and birthdates were replaced with unique, randomized tracking IDs. This ensures that while we can track the movement and performance of specific serial entrepreneurs and investors across the universe of UK firms, the underlying personal data remains fully anonymized within our research sample. Our final dataset comprises a comprehensive panel of the universe of UK incorporated firms, mapping their real activity, managerial composition, and financing from 2002 through 2024.

We begin by documenting the prevalence and composition of LTD across the firm lifecycle, focusing specifically on the distinction between CF-LTD and A-LTD. A striking feature of the UK corporate universe is the significance of the extensive margin: approximately 50% of firms never access long-term debt markets during our sample period. For those that do, financing is heavily tilted toward CF-LTD, especially during the early stages of the lifecycle.

As shown in Figure 1a, approximately one-quarter of all firms obtain LTD at start-up (age 0). Among these early borrowers, the overwhelming majority (94%) utilize

CF-LTD, while only 6% rely on A-LTD. This dominance persists as firms mature; by age 10, 83% of firms that have levered continue to use CF-LTD exclusively, while only 2% rely solely on A-LTD and 15% utilize both. Even by age 19, 72% of firms maintain exposure only to CF-LTD. Crucially, this is not merely a small firm phenomenon. Figure 1b shows that in the top decile of firms by employment at start-up, 88% of those with debt at start-up use CF-LTD. While older firms are more likely to eventually diversify their financing—with 60% of the top decile using both types by age 19—a significant share of even the largest firms never moves beyond cash-flow-based lending.

We focus our analysis on the first lending event for two primary reasons. First, for the majority of firms, the initial entry into the debt market is the most significant financing milestone in their lifecycle. Second, we observe a high degree of path dependency: transitions between debt types are rare. As noted above, nearly three-quarters of firms remain exposed to only one form of debt even after nearly two decades of operation. This suggests that the initial choice of debt type is a fundamental differentiator that characterizes a firm's long-run trajectory.

The modal timing for entering the credit market is at inception. Table 1 displays the count of firms by timing of when they receive their initial LTD financing. We find that 26% of all firms in the universe secure LTD at age 0. Conditional on a firm ever receiving long-term debt, 53% do so at start-up. This propensity to borrow at inception is consistent across both debt categories: 52% of firms that eventually use CF-LTD and 61% of those that eventually use A-LTD secure their first loan at age 0. While the probability of receiving first-time financing decreases as firms age, a significant proportion of survivors obtain their first credit facility later in their lifecycle, providing the temporal variation we exploit to study the effects of debt timing on long-run outcomes.

3 Results

3.1 LTD at start-up as predictor of firm performance

We first investigate whether the acquisition of Long-Term Debt (LTD) at inception serves as a robust predictor of long-run firm performance, even after conditioning on a comprehensive set of observable start-up characteristics. To do so, we estimate the following cross-sectional specification:

$$\log(\text{Employment}_{i,A}) = \alpha + \beta \mathbb{1}(\text{LTD}_i > 0)_{t=0} + \Gamma \mathbf{X}_{i,0} + \epsilon_i \tag{1}$$

where $A \in \{10, 19\}$ represents the firm's size at age 10 or 19, and $\mathbf{X}_{i,0}$ is a vector of initial observables measured at the time of the firm's first appearance in the BSD. This vector includes combinations of log assets, log employment, log turnover (as a proxy for initial cash flow), and labor productivity.

As reported in Table 2, we find a consistent and statistically significant positive association between initial LTD receipt and future firm size. In our most stringent specification we find that firms that secure long-term debt at start-up are approximately 20% larger at age 10 and 19% larger at age 19. This persistent size differential suggests that early-stage LTD issuance contains significant private information regarding a firm's long-run growth potential. This forward-looking component of lending implies that financial intermediaries effectively screen for high-quality entrants. Crucially, this predictive power is primarily concentrated in CF-LTD.

3.2 Timing of initial LTD and firm performance

We investigate whether the specific age at which a firm first accesses the long-term debt market predicts its long-run scale. To allow for potential non-linearities in this relationship, we estimate a non-parametric specification that regresses log employment on a vector of indicator variables representing the firm's age at its first lending event:

$$\log(\text{Employment}_{i,A}) = \alpha + \sum_{k=1}^{9} \beta_k \mathbb{1}(\text{AgeFirstLTD}_i = k) + \Gamma \mathbf{X}_{i,0} + \epsilon_i \tag{2}$$

where $A \in \{10, 19\}$ denotes the firm's size at age 10 or 19. The term $\mathbb{1}(\text{AgeFirstLTD}_i = k)$ is an indicator for the firm receiving its first long-term debt at age $k \in \{0, \ldots, 9\}$, with age 0 (debt at inception) serving as the omitted baseline category. We estimate this model for the full sample of firms with debt and then separately for those whose first debt event is either CF-LTD or A-LTD. Table 3 presents the results and figure 3 has the corresponding coefficient plots with standard errors.

For the CF-LTD subsample, we find a large and statistically significant negative coefficient for β: firms that secure CF-LTD earlier in their lifecycle exhibit significantly steeper growth trajectories. Specifically, firms obtaining their first CF-LTD at age 1 are, on average, 15% larger by age 19 than firms that first access this financing at age 5.

In stark contrast, these patterns do not extend to Asset-Backed LTD (A-LTD). When estimating Equation 2 for the A-LTD subsample, the coefficients on the age of first financing is statistically indistinguishable from zero. We further confirm that this divergence in patterns is not just visible for employment, but also for turnover and assets.

This divergence implies that the forward-looking informational content of early-stage debt is unique to cash-flow-based contracts. To ensure these results are not sensitive to the choice of terminal age, we provide extensive robustness checks in the Appendix. We replicate our primary analysis using alternative outcome variables, specifically log employment 5 years and 10 years after the initial financing event. These results, reported in Figure B5, confirm our results.

3.3 Decoupling CF-LTD lending from screening

Our previous results are consistent with the idea that lenders perform a forward-looking assessment of firm value in CF-LTD lending, extending credit only to those entrepreneurs whose expected productivity and future cash flows surpass a specific quality threshold.

The Bounce Back Loan Scheme (BBLS), introduced by the UK government in May 2020 and closed to new applications on March 31, 2021, provides a unique setting to test the value of this screening channel by exogenously suspending it. For our analysis, we define two cohorts based on the policy cutoff: eligible firms are those incorporated prior to March 1, 2020, while ineligible firms are those incorporated on or after that date.

Because administrative entry in the Business Structure Database (age 0) typically occurs approximately one year after a firm's legal incorporation, we perform our initial observation of financing status and firm scale at this one-year mark. To isolate the effects of lender screening from the direct effects of finance, we perform our RDD analysis three times: once for the aggregate sample, and twice more by partitioning the sample into firms that secured long-term debt at inception (Users) and those that did not (Non-Users). This allows us to test our quality predictions within financing status. While we observe initial financial conditions at age 0 to determine if firms accessed BBLS-era credit, our primary comparisons of real outcomes focus on age 3 – the 2024 end of our sample – to evaluate how initial lender screening correlates with medium-run trajectories.

We hypothesize that BBLS eligibility induced a negative selection effect. Specifically, when comparing firms that secured credit (Users), we expect the ineligible cohort to exhibit higher latent quality because they were subjected to standard, forward-looking bank screening filters, whereas eligible borrowers secured credit via a non-discretionary government guarantee. Conversely, when comparing firms that did not secure credit (Non-Users), we expect the ineligible cohort to also exhibit higher quality. This is because the ineligible non-user pool likely contains high-potential firms that had not yet established a sufficient signal to pass stringent private screening during the pandemic. In contrast, the absence of screening for the eligible cohort suggests that nearly any viable firm with a demand for credit would have secured a BBLS loan, leaving only the lowest-quality or least ambitious firms in the eligible non-user pool.

The BBLS represented a significant departure from traditional commercial lending. The government provided lenders with a 100% guarantee on the lending risk, effectively

removing the private sector's incentive to screen for borrower viability. To prioritize the speed of capital disbursement, lenders were not required to perform standard credit or affordability checks, relying instead on borrower self-certification (National Audit Office 2020, UK Government 2020). The facility was highly subsidized: loans were capped at 25% of turnover (up to £50,000), with 100% of the lending risk assumed by the government.

We utilize the March 1, 2020, cutoff to implement a Regression Discontinuity Design (RDD) using granular incorporation dates to estimate the following local linear specification:

$$Y_i = \alpha + \beta \text{Ineligible}_i + \gamma_1(z_i - c) + \gamma_2 \text{Ineligible}_i(z_i - c) + \epsilon_i \tag{3}$$

where Y_i is the outcome for firm i and $(z_i - c)$ is the running variable (months from the March 1st cutoff). The coefficient β identifies the local average treatment effect (LATE) of being ineligible for the BBLS. We estimate this model for the full sample (Panel 1), the Non-User sub-sample (Panel 2), and the User sub-sample (Panel 3), using a six-month bandwidth.

Table B2 reports the RDD estimates. In the aggregate (Panel 1), we find a sharp discontinuity in credit access at the point of administrative entry: ineligible firms were 8.8 percentage points less likely to secure long-term debt (Column 1) and had 63% less debt on the intensive margin (Column 2). Despite this substantial reduction in available capital, real outcomes at age 3 (Columns 3–5) remain statistically indistinguishable across the cutoff. Most strikingly, Column 6 shows that ineligible firms exhibit a 5 percentage point higher survival probability.

The partitioned results in Panels 2 and 3 clarify that this survival advantage is driven by the selection mechanisms within financing groups. For Non-Users (Panel 2), the ineligible cohort exhibits a nearly 10 percentage point higher survival probability (0.098^{***}). This supports our hypothesis that the ineligible non-user pool retained high-quality firms that were simply waiting to build a credit signal, whereas the eligible non-user pool was depleted of viable firms by the low-barrier BBLS. For Users (Panel

3), while the survival jump is smaller (0.013), the comparison of means in Table B1 shows that Ineligible Users – who passed bank screening – exhibited superior growth trajectories. Although they started at a smaller scale at age 0 (0.528 vs. 0.603 in log employment), by age 3 they surpassed the eligible cohort in mean log employment (0.876 vs. 0.864) and turnover (5.290 vs. 5.257).

The comparison among firms that did not secure debt (Non-Users) further reinforces this selection mechanism. Ineligible Non-Users exhibited positive employment growth from Age 0 to Age 1 (0.483 to 0.562). In contrast, Eligible Non-Users saw their mean scale decline over the same period (0.599 to 0.569). This divergence suggests that the eligible non-user pool was depleted of its most viable members by the low-barrier BBLS facility, whereas the ineligible non-user pool retained high-quality firms that were unable to clear the high private-bank screening threshold at inception. Collectively, these findings demonstrate that when credit allocation is decoupled from the forward-looking assessment of the screening channel, the predictive link between initial financing and subsequent long-run scaling is severed.

3.4 Empirical predictions

Our previous results establish that in CF-LTD lending, lenders typically perform a forward-looking assessment of firm value, extending credit only to those entrepreneurs whose expected productivity and future cash flows surpass a specific quality threshold. To formalize the link between this screening process and observed firm trajectories, we introduce a tractable partial information setting within our lending model. In this framework, lenders attempt to observe a signal of the firm's future productivity, Z, but face varying degrees of information friction. When the future signal is noisy, the lender's expectation of long-run value shrinks toward the firm's current observed signal, z. As the correlation between the available signals and true future productivity weakens, the lender must rely more heavily on current earnings as a proxy for viability.

This structure generates a lending threshold that depends not only on credit rationing conditional on observing future value, but also on the precision of the lender's learning

process. As the ability to learn about Z above and beyond current z diminishes – a scenario we denote as an increase in the information friction parameter ρ – the selection mechanism shifts. Specifically, as ρ converges to 1, the lender's ability to differentiate firms based on long-run potential vanishes. The threshold flattens out in this limit, and we recover the lack of long-run selection characteristic of an asset-based or purely earnings-based constraint. In our framework, the transition from tangible to intangible sectors, or from familiar to foreign industries for serial entrepreneurs, is mapped directly to an increase in this ρ parameter.

We hypothesize that screening is inherently more difficult in cases where future value is less observable from current signals, leading to two distinct arguments for empirical verification based on the variation in ρ.

First, in intangible-intensive sectors, the lower reliance on physical capital and the high idiosyncratic risk of R&D-driven growth create a noisier informational environment (higher ρ). Because the value of intangible assets is often embedded in human capital or proprietary knowledge that is difficult for a third party to verify, current earnings z serve as a noisier proxy for future Z. To mitigate this uncertainty, lenders apply a more stringent selection filter. Only firms with exceptionally high latent productivity can generate a signal strong enough to overcome the noise and clear the financing hurdle. Consequently, the model predicts that conditional on securing CF-LTD, intangible firms will start at a smaller initial scale due to tighter credit rationing but will exhibit significantly faster growth and higher long-run survival as a result of this superior selection on Z.

Second, a similar informational friction exists for serial entrepreneurs switching to a new industry, representing a discrete jump in ρ compared to those staying in a familiar sector. While serial entrepreneurs who stay within their original industry can leverage a verifiable track record and industry-specific reputation, those who switch industries present a broken signal to lenders. The soft information and reputation accumulated in the previous sector do not fully transfer, making it harder for lenders to identify high-ability entrepreneurs. Facing this increased noise, lenders again shrink their expec-

tations toward the current signal, requiring switchers to pass a tougher quality test to secure credit. The model thus predicts that switchers will start smaller than their non-switching counterparts but will exhibit steeper growth trajectories and ultimately higher performance, as only the highest-quality entrepreneurs are able to secure financing in a foreign industry.

These patterns are critical because they would not emerge in a purely earnings-based constraint model. In a model where lending is determined strictly by current z, firms that start small would not systematically grow faster or eventually outperform larger firms. By highlighting these divergent trajectories for intangibles and serial entrepreneur switchers, we provide empirical evidence that lender screening in CF-LTD markets effectively filters for latent quality. This selection effect is strongest precisely when the informational environment is most challenging, confirming that lenders engage in learning to identify long-run firm value.

4 A Tractable Model

We build a theory to guide our understanding of the patterns keep in the data which highlight the need for forward-looking financing.

We view our specification as applicable to more general forms of financing beyond long term debt which may include equity injections. In particular, venture capital investments early on in the firm life cycle are often based on little information on current assets nor cash-flows and all about expectations of future cash-flows embedded in the valuation of firms at the time of financing.

As it turns out, to be able to rationalize many of the patterns seen in the data, we need a forward-looking lending constraint. A current earnings-based based borrowing constraint is not enough as it resembles the backward looking constraint. Such forward-looking constraint is appealing because it allows for potential "superstars" to access the financing they need to survive today.

4.1 Setup

In this section, we develop a tractable model of asset vs value based financing which can be viewed as a two-period version of Melitz (2003) with financing frictions.

There are two periods. Firms have two different productivities today z and tomorrow Z. Firms survive to the next period if they choose to continue to operate in the first period. Firms hire labor and produce with a Cobb-Douglas technology subject to an operating cost giving rise to the following flow profit function:

$$\pi(z) = \max_{l} z^{1-\alpha} l^{\alpha} - wl - f = \kappa z - f$$

Where the second equality comes from optimizing out labor and defining a constant $\kappa = \kappa(w) = (1-\alpha)(\alpha/w)^{\frac{\alpha}{1-\alpha}}$. We assume the steady-state Z follows a Power Law with exponent ζ and minimum $\underline{Z}$: $Z \sim G(Z) = 1 - (Z/\underline{Z})^{-\zeta}$. The transition from z to Z is governed by a Markov process $F(z, Z)$. Firms borrow and have dividends. Negative dividends are equity. Firms are born with a stock of debt b. If b is positive, they need to pay it back. b negative are assets firms receive. If the firm exits at any point they receive back their net asset positions. When a firm borrows it receives a face value $b'/(1+r)$ which they must pay back tomorrow as $-b'$.

$$d_0 = \pi(z) - b + \frac{b'}{1+r}, \quad d_1 = \pi(Z) - b'$$

Unconstrained decision. A firm chooses whether to survive or not in every period as well as how much to have as dividends or debt.

$$v(z, Z, b) = \max_{d, b'} \left\{ \pi(z) - b + \frac{b'}{1+r} + \frac{1}{1+r} \left(\mathbb{E}_{Z|z} \max\{\pi(Z), 0\} - b' \right), -b \right\}$$

In the case where a firm is not financially constrained, then since $\frac{b'}{1+r} - \frac{b'}{1+r} = 0$ we have that the split between d, b' is indeterminate (a version of Modigliani-Miller).

Regardless, the survival choice is independent of b, and the value function:

$$v\left(z,Z,b\right)=\max_{d,b'}\left\{\pi(z)+\frac{1}{1+r}\mathbb{E}_{Z|z}\pi(Z)\right\}-b=v\left(z,Z\right)-b$$

Lemma 1. Absent financial frictions, if Z is know to firms, firms will survive today if $(z|Z)$ is such that:

$$z^{*}(Z)=\begin{cases}\frac{f}{\kappa} & \text{if } Z<Z^{*}\equiv\frac{f}{\kappa} \text{ firms exits when young}\\ \frac{f}{\kappa}\cdot\frac{2+r}{1+r}-\frac{Z}{1+r} & \text{otherwise firm survives to old age}\end{cases}$$

Intuitively, if the firm knows itself to be a future superstar it will weather a stronger negative z today. Given this formulation, there are future superstar firms with productivity so high $Z\geq Z^{*}=\frac{f}{\kappa}\left(2+r\right)$ such that $0=z^{*}\left(Z^{*}\right)$ and hence, will find it always profitable to survive regardless of their current draw.

Proof. See Appendix.

Asset-Based Constraint. Firms decide whether to exit today or not and whether to borrow to weather the shock given the following problem subject two a non-equity issuance constraint $d\geq 0$ and a borrowing constraint on b' based on the assets the firm can pledge as collateral.

$$v\left(z,Z,b\right)=\max_{d,b'}\left\{d+\frac{1}{1+r}\mathbb{E}_{Z|z}v(Z,b'),-b\right\}$$

$$v(Z,b')=\max\left\{\pi(Z)-b',-b'\right\}$$

$$d=\pi(z)-b+\frac{b'}{1+r}\geq 0$$

$$b'\leq\chi b$$

Lemma 2. Given an asset based constraint, the survival threshold depends on b only:

$$z\geq z_{b}(b)\equiv\frac{f}{\kappa}+\bar{\Gamma}\frac{b}{\kappa}\equiv\frac{f}{\kappa\left(w\right)}+\left(1-\frac{\chi_{b}}{1+r}\right)\frac{b}{\kappa\left(w\right)}$$

and thus, the asset-based constraint prevents the forward-looking selection on Z happening in the frictionless case.

Proof. See Appendix.

Current Cashflow-Based Constraint. If instead of an the last asset-based constraint above, firms can borrow against a multiple of current cash-flows in an earning based borrowing constraint, we will have:

$$b' \leq \chi_\pi \pi(z)$$

Lemma 3. The current earnings based constraint is essentially isomorphic to an asset based one. In essence, the exit threshold still depends on b and is independent on Z – whether the firm is going to be a superstar or not – and only depends on their current assets.

$$z \geq z_\pi(b) = \frac{f}{\kappa} + \bar{\Gamma}_\pi \frac{b}{\kappa}, \quad \text{s.t.} \quad \bar{\Gamma}_\pi = \left(\frac{1+r}{1+r+\chi_\pi}\right)$$

Proof. See Appendix.

Value-Based Constraint.

Alternatively, consider the case of a firm with a value based constraint where:

$$b' \leq \chi_v \mathbb{E}_{Z|z} v(Z, b')$$

We interpret χ_v – our parameter of interest – as both the ability to screen firms value or ability to lend to firms conditional after screening which may be impaired by financial technology or regulation frictions we leave unmodeled.

Under perfect information, the financier would be able to observe Z. With no information, the lender could try to infer Z from current z or infer this value from a population known to be Power Law.

As an illustrative case, when financiers have an imperfect process of observing future

productivity that follows:

$$z'|z, Z = \begin{cases} z & \text{with probability } \rho \\ Z & \text{with probability } 1-\rho \end{cases}$$

Hence, the process for productivity has effective persistence ρ of past z with a drift related to the long-run Z: $\mathbb{E}\left(z'|z, Z\right) = (1-\rho)\, Z + \rho z$.

Proposition 1.

Under a perfect information value based constraint, we can drop the expectation because Z is known and the threshold depends on both b and Z.

$$z \geq z_v\left(b, Z\right) = \frac{b}{\kappa} + \frac{f}{\kappa} - \frac{1}{(1+r)} \frac{\chi_v}{1+\chi_v} \max\left\{Z - \frac{f}{\kappa}, 0\right\}$$

Hence, the value-based constraint reintroduces forward-looking selection because borrowing depends on future Z. Note that there is still a high enough value of $Z^* > \frac{f}{\kappa}$ such that $z_v\left(b, Z^*\right) = 0$ i.e. where very productive firms will always be able to remain in operation regardless of how bad their current conditions are, although in general higher than in the frictionless economy. Further, as $\chi_v \to \infty$ the slope of the threshold function with respect to Z approaches that of the frictionless economy.

Under no information about the future profitability of firms we have:

$$z \geq z_{\bar{v}}(b) = \bar{\Gamma}_v \frac{f}{\kappa} + \frac{b}{\kappa}, \quad \bar{\Gamma}_v = 1 + \frac{\chi_v}{1+\chi_v} \frac{1}{(1+r)} \frac{\left(\underline{Z}\right)^{\zeta} \left(\frac{f}{\kappa}\right)^{-\zeta}}{\zeta - 1} < 1$$

That is, we recover a version of the asset-based constraint with $\bar{\Gamma}_b = 1$ and a $\bar{\Gamma}_v$ that amplifies the effect of the fixed cost. In this extreme case, however, we would expect convergence to the same point like the case of the asset-based constraint. Then, the extent to which the degree of selection depends on long run Z could be informative about the lending technology.

Figure 5 plots all the survival thresholds for today's productivity as a function of future productivity for a given b. It highlights visually that Proposition 1 with Lemmas 1-4 together show the powerful result that a perfect information value-based constraint

yields a cutoff that depends on forward-looking productivity Z type, like the frictionless cutoff, but with different intercept tied to b and slope. In contrast, backward asset based, current earnings based, and no-information value based constraints are all isomorphic in the sense that all do not depend on Z at all, but have different intercepts tied to b.

Proposition 2. Lenders have an imperfect technology to infer Z given data on z (we assume for tractability b cannot be used in the inference). Then $z \geq z_v^i(b, Z)$ where the threshold becomes a fixed point of the following equation.

$$z_v^i = \frac{b}{\kappa} + \left(1 + \frac{\chi_v}{1+\chi_v}\frac{\mathbb{P}^*\left(z_v^i, Z\right)}{1+r}\right)\frac{f}{\kappa} - \frac{\chi_v}{1+\chi_v}\frac{\mathbb{P}^*\left(z_v, Z\right)\mathbb{E}^*\left(z_v, Z\right)}{1+r}$$

Under the simplification with ρ, the threshold collapses to:

$$z_v(Z,b) = \begin{cases} \frac{f}{\kappa} + \left[1 + \rho\frac{1}{1+r}\frac{\chi_v}{1+\chi_v}\right]^{-1}\frac{b}{\kappa}, & \text{if } Z \leq \frac{f}{\kappa}, \\ \frac{f}{\kappa} + \left[1 + \rho\frac{1}{1+r}\frac{\chi_v}{1+\chi_v}\right]^{-1}\left[\frac{b}{\kappa} - \frac{1}{1+r}\frac{\chi_v}{1+\chi_v}(1-\rho)\left(Z - \frac{f}{\kappa}\right)\right], & \text{if } \frac{f}{\kappa} < Z < \frac{f}{\kappa} + \frac{\frac{b}{\kappa}}{\frac{1}{1+r}\frac{\chi_v}{1+\chi_v}(1-\rho)}, \\ \frac{f}{\kappa} + \frac{b}{\kappa} - \frac{1}{1+r}\frac{\chi_v}{1+\chi_v}(1-\rho)\left(Z - \frac{f}{\kappa}\right), & \text{if } Z \geq \frac{f}{\kappa} + \frac{\frac{b}{\kappa}}{1+r}\frac{\chi_v}{1+\chi_v}(1-\rho). \end{cases}$$

Proof. See Appendix.

The intuition for Proposition 1 is simple but powerful. Under the value-based constraint, future Z can enter the valuation today and affect firms' borrowing capacity. When financiers can only imperfectly observe Z, we have two parameters to shock: ρ or how difficult is it to observe Z and χ_v even after making an inference about the valuation, how easy is it to lend to lend to seemingly valuable firms. There are three key regions: (1) when $Z \leq f/\kappa$, there's no possible future since the firm will not continue. z_v is flat in Z, (b) when $Z > f/\kappa$, the promise of future cashflows help the firm borrow today. z_v falls with Z, (c) eventually, $z_v \leq f/\kappa$. This means that the firm will survive even if their current cashflows are negative.

When $\rho \to 0$ we get the perfect information case. When $\rho \to 1$ we recover a version of the earnings-based constraint is recovered. For ρ in between, the relationship between the threshold and z weakens with information frictions, but remains present in the model to the extent that lenders are able to estimate steady-state Z with some

degree of accuracy. Figure 5 makes this point showing that as information becomes more imperfect, the value-based constraint converges to the earnings based constraint. But as the quality of information financiers are able to extract on future Z improves, the threshold schedule resembles more and more the shape of the frictionless environment.

4.2 Employment life cycle with value based financing

Figure 6 shows how average firm employment evolves from entry (Young) to maturity (Old) under two different lending regimes, for firms that start at different initial sizes: i.e. firms that happen to draw different productivity levels at entry. We also show the effect of credit tightening from a lower χ in each environment.

In the case of backward-looking asset-based lending, despite starting at very different sizes, the two firms converge to identical steady-state employment consistent with the view that asset-based lending makes firms appear as if they were ex-ante identical (as in Hopenhayn (1992)) even if they are not. The reason is mechanical: the asset-based lender sets a single survival threshold that depends only on the firm's collateral, not on where it is headed. All firms that make it through selection were screened against the same bar, so the surviving pool has the same average productivity regardless of what the firms looked like at entry. Initial size is completely irrelevant to mature size.

In the case of forward-looking value-based lending, the gap that existed at entry persists into maturity. This happens because the value-based lender sets a threshold that varies with the firm's expected future productivity — firms with better prospects face a lower bar. So the two firms, even though they face the same lender, are selected from pools with different thresholds, and therefore different conditional means at maturity. The initial difference in productivity partially maps into a steady-state difference in size in the long run: as in Melitz (2003), value-based lending results in firms being ex-ante heterogeneous.

Figure 6 also captures another striking feature of the data, which is that in more intangible-intensive sectors – where potentially it is harder to assess the forward looking value of firms or χ_v is low, average employment growth is faster. This is not due to

each firms growing faster with financial frictions, rather than due to the distributional consequences of financial frictions. When χ falls, the threshold rises, implying better selected firms who end up growing larger in the steady state as credit tightens. Young firm's employment will also be affected in the richer model where entrant's size (and not just their survival to old age) depends on the financing technology.

Finally, of note, the simple model implies that as value-based financing frictions tighten, we should expect to see convergence in firm types in the steady state.

4.3 Aggregation and productivity with value based financing

There is a rich interplay between finance and aggregate productivity even in this very simple model of heterogeneous firms and dynamic selection as shown in Figure 7.

For example, in the extreme, if $b = 0$, there is no borrowing possible under an asset based constraint as in Sterk et al. (2021). However, under a value based constraint, some borrowing is allowed based on firm productivity and hence, there are TFP gains from alleviating such frictions even in an economy with extremely low levels of wealth as Figure Z points out. Figure A also shows that the elasticity of TFP to changes in financing capacity can be much larger for value-based constraints in markets that are relatively less financially developed at baseline. In contrast, tackling asset-based constraints may yield slower changes in TFP, and these may depend on the distribution of wealth among entrepreneurs to begin with.

Further, we can also see in Figure 8 that whether frictions arise from simply a tighter constraint (lower χ) versus worse information about future Z (higher ρ) leads to significantly different changes in selection. The later will lead to both a stronger crowding-out of superstars (top Z) with unlucky today as well as the crowding-in of worse future firms that had lucky outcomes today. Figure 9 confirms that the fast aggregate TFP benefits as credit conditions are relaxed (higher χ) vanishes when information about future Z worsens (higher ρ) due to the crowding-in of lower z firms and the crowding-out of high Z firms.

5 Richer Calibrated Model

We embed our tractable framework into the canonical model of firm life cycle dynamics from Sterk et al. (2021) which allows for firms to be ex-ante heterogeneous as in Melitz (2003) retaining ex-post shocks as in Hopenhayn (1992). While Sterk et al. (2021) study a simple (no-borrowing) friction, we study more complex asset-based and value-based constraints with the goal of understanding the UK data patterns discussed earlier.

5.1 Setup

The economy is populated by firms that produce differentiated goods using a linear technology with a fixed operating cost.

$$y_i = n_i - f$$

Each good is has a demand function with an ideosyncratic demand shifter φ_i which we can be interpreted as the stochastic customer capital a firm accumulates over time.

$$y_i = \varphi_i \left(\frac{p_i}{P}\right)^{-\xi} Y$$

The price and output indices depend on the endogenous set of firms active in equilibrium Ω_t.

$$P \equiv \left[\int_{i\in\Omega_t} \varphi_i p_i^{1-\xi} di\right]^{\frac{1}{1-\xi}}, \quad Y \equiv \left[\int_{i\in\Omega_t} \varphi_i^{\frac{1}{\xi}} y_i^{1-\frac{1}{\xi}} di\right]^{\frac{\xi}{\xi-1}}$$

We set $W = 1$ as the numeraire and let $w = 1/P$ be the real wage. The budget constraint must hold $\int_{i\in\Omega_t} p_i y_i di = WN + \Pi$. The later reflects the flow profits of each firms:

$$\pi_i = p_i y_i - W n_i$$

In equilibrium firms ideal hiring decision tracks productivity:

$$n_i = \varphi_i \left(\frac{\xi}{\xi - 1}\right)^{-\xi} w^{-\xi} Y + f$$

Letting $\chi \equiv \frac{(\xi-1)^{\xi-1}}{\xi^{\xi}}$ we can express profits as

$$\pi_i = \varphi_i \chi w^{-\xi} Y - f$$

We let firms borrow or lend in a financial asset b_i. We assume firms start with a distribution of assets b_0. The value of the firm net of their asset position is:

$$V(a,b) = \max\left\{0, E\left[\pi\left(a'\right) + \beta(1-\delta)\int_{\varphi(a',b')\geq\varphi^*(a,b)} V\left(a',b'\right) dF\left(a' \mid a\right)\right]\right\}$$

Where firms have a bankruptcy threshold. We follow Sterk et al (2021) in allowing assets to accumulate via

$$b' = (1+r)\left(b + \pi\left(a'\right)\right)$$

This emerges from imposing a non-negative dividend constraint that binds with equality:

$$d = \pi(a') + b - b'/(1+r) \geq 0$$

Note that initially in the firms' life $\pi\left(a'\right) < 0$ due to the presence of the costs of operations and low initial productivity.

We first think of two segments of the economy (e.g. tangible vs intangible sectors) one of which borrows using secured and the other unsecured financing. The presence of the constraint affects the forward looking value of firms.

Note the baseline Sterk et al. (2021) impose an exogenous borrowing constraint $b_i \geq -\chi_0$ where $\chi_0 \geq 0$ (in their solution imposing essentially no-borrowing $\chi_0 = 0$. We instead allow for the constraint to evolve endogenously with the rest of the firms' problem and study its economic consequences. Like Sterk et al. (2021) assume, as we did in the tractable model, we assume that if at any point in time the firm cannot meet this limit, it is forced to exit (i.e. default).

Value-based lending. Firms can borrow up to a multiple of their value. The intuition is that the lender may be able to recover the intangible value of the firm in the event of default, inherently operating the firm as an entrant with the same technology

and current assets. We impose that the firm and the lender have the same expectations emphasizing uncertainty rather than relying on information asymmetry. This additional constraint inherently acts as a discount rate wedge.

$$b_i' \geq -\chi_u \mathbb{E}V\left(a_i', b_i'\right)$$

As a result, relatively high long-run value firms will be less likely to exit, but at the same time, temporary shocks that drive down the value of firms will affect exit.

Asset-based lending. Firms may borrow up to a fraction $\chi_s \geq 0$ of their current assets. As firms accumulate baseline b_i, they start to be able to borrow in the event of negative shocks. The intuition is that the lender may be able to recover a fraction of the assets of the firm in the event of default.

$$b_i' \geq -\chi_s b_i$$

High current productivity firms a_i with lower assets b_i will be forced to exit.

Earnings-based lending. As an alternative, we have

$$b' \geq -\chi_\pi \pi(a_i')$$

We impose a free entry condition under fixed entry costs f^e and an entrant distribution of a, b.

$$w \cdot f^e = \iint V(a,b) dG(a,b)$$

The endogenous distribution of firms over productivity and assets evolves according to the exogenous productivity process and the endogenous exit and entry process, as well as the accumulation of assets among firms.

$$\mu\left(a', b'\right) = \int \int [1 - X(a,b)] 1(b' = b'(a,b)) F\left(a' \mid a\right) \left[(1-\delta) d\mu(a,b) + M_e dG(a', b')\right]$$

Further, we enforce labor market clearing with fixed labor supply, where part of the labor demand goes to production and part towards investment into paying the entry and operating costs.

$$\bar{N} = \int y\left(a,b\right) d\mu\left(a,b\right) + \int f[1 - X(a,b)]\left[d\mu(a,b) + M_e G(da,db)\right] + M_e f^e$$

In this richer version of the model, aggregate productivity is endogenous and is tied to both the wage and the number of entrants, both endogenous objects solved in general equilibrium to solve free entry and labor market clearing jointly.

$$w = P^{-1} = \left(\frac{\xi - 1}{\xi}\right)\left(M_e \bar{\varphi}\right)^{\frac{1}{\xi - 1}}, \quad \text{where,} \quad \bar{\varphi} \equiv \int \varphi(s)\hat{\mu}(ds)$$

Note because the risk-free asset can also be held by households $r = 1/\beta - 1$.

This closes the description of the model.

5.2 Main Calibration and Counterfactual

We follow Sterk et al (2021) and let firms have

$$\ln \varphi_i = u_{i,t} + v_{i,t} + w_{i,t} + z_{i,t}$$

$$a_{i,t} = (\theta_i, u_{i,t}, v_{i,t} + w_{i,t}, z_{i,t})$$

$$\begin{aligned}
u_{i,t} &= \rho_u u_{i,t-1} + \theta_i, & u_{i,-1} &\sim \text{iid}\left(\mu_{u^e}, \sigma^2_{u^e}\right), \quad \theta_i \\
v_{i,t} &= \rho_v v_{i,t-1}, & v_{i,-1} &\sim \text{iid}\left(\mu_\theta, \sigma^2_\theta\right), \quad |\rho_u| \leq 1, \\
w_{i,t} &= \rho_w w_{i,t-1} + \varepsilon_{i,t}, \quad w_{v^e}\right), & |\rho_v| &\leq 1, \\
z_{i,t} &\sim \text{iid}\left(0, \sigma^2_z\right). & \varepsilon_{i,t} &\sim \text{iid}\left(0, \sigma^2_\varepsilon\right), \quad |\rho_w| \leq 1,
\end{aligned}$$

We calibrate this productivity process and constraint parameters in the model jointly

to match average size-by-age and average exit-by-age profiles for the UK economy in Figure 10.

While we do not directly target this in the calibration, the model with the forward-looking (value-based) constraints matches the patterns of unsecured lending: firms that borrow earlier converge to higher long-run points as shown in Figure 10. Figure 11 shows that with the backward-looking (asset based) constraints the patterns of secured lending emerge: firms converge to the same point regardless of when they start borrowing; differences in initial positions map to differences in asset-values used for collateral, not to long-run differences in firm quality as with unsecured financial frictions.[3] This resembles the patterns found in the tractable model but in a richer environment where firms can live for more than two periods and with a much richer firm dynamics environment.

Further untargeted, we find that lending leads to lower predictability of future size relative to the initial size of firms.

With the calibrated model study the effects of differences in value-based financial frictions i.e. changing χ_u. Tightening financial frictions lead to (as expected) depressed aggregate output and productivity mainly due to their effect on the number of firms in the economy. As the value based constraint tightens, exit rate rises but at the same it crowds out higher future productivity firms due to the negative selection mechanism described in the toy model. This leads to slower growth rates of employment, resembling the differences between the UK and the US that motivated our analyses.

We repeat the exercise of comparing an economy with and without ex-ante heterogeneity as in Sterk et al. (2021). We find that for the same degree of ex-ante heterogeneity in productivity, the value-based constraint generates a wider long-run inequality among firms than an asset-based constraint. This is natural given the fact that the life cycle paths of firms stay ranked throughout their lives as opposed to converging to the same point. This difference in long-run inequality between the two economies only arises with ex-ante heterogeneity: with only ex-post heterogeneity, the two economies are virtually

[3]However, the effects relative to an asset-based constraint economy are subtle due to the fact that the value-based constraint may induce a higher level of baseline efficiency (and thus, minimize the efficiency gains).

indistinguishable.

We are currently exploring these and other patterns further and will present results in a future version of the paper.

6 Conclusion

We document that the timing of firms' access to cash-flow based long-term debt is a powerful predictor of their long-run performance. Firms that obtain this form of financing earlier go on to grow larger and follow more unequal trajectories than otherwise similar firms, while the timing of access to asset-backed debt has little relation to long-run outcomes. To interpret these facts, we develop a tractable framework in which financing decisions depend both on collateral and on signals about firms' future value. The model helps explain why forward-looking financing is associated with strong predictability in the data and highlights how frictions in different credit markets shape firm dynamics. Simulating a richer, calibrated model shows that reducing frictions to forward looking financing in the UK would lead to more US-like unequal firm dynamics, including a larger number of "superstar firms".

Taken together, our results suggest that the structure of financing constraints plays a central role in determining which firms grow and survive, with important implications for aggregate outcomes. Policies or market developments that ease access to forward-looking financing can foster faster growth and a greater prevalence of high-performing firms, but may also increase inequality in firm size and performance. More broadly, understanding how different forms of credit interact with firm heterogeneity is essential for evaluating the consequences of financial development for economic dynamism.

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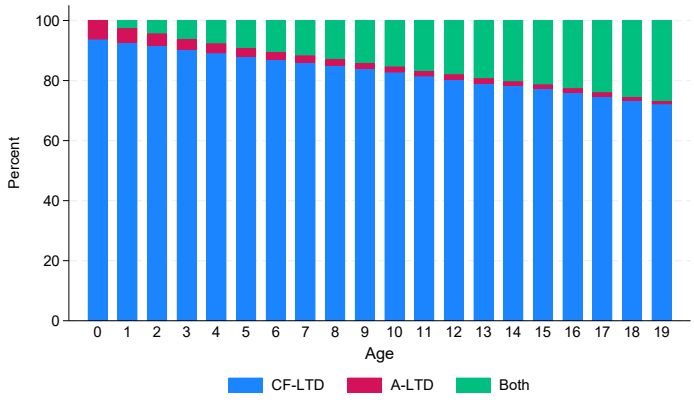
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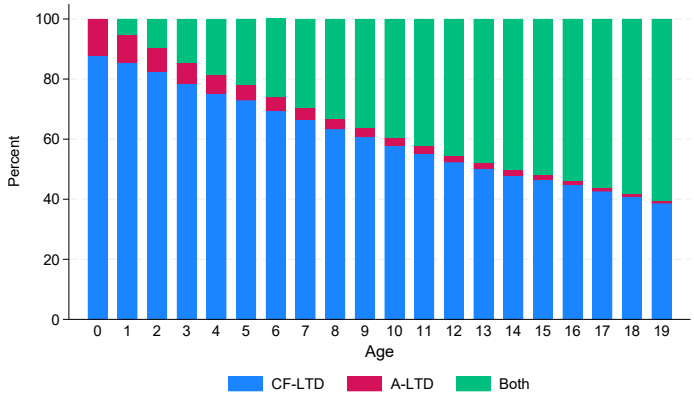
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Figures



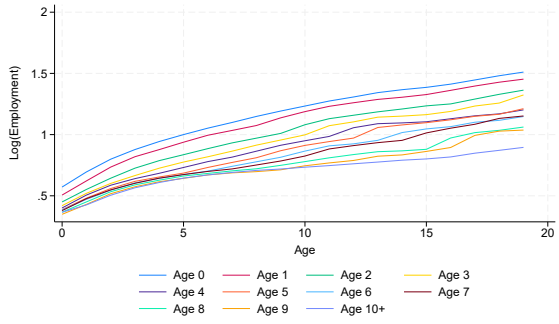
(a) Full sample



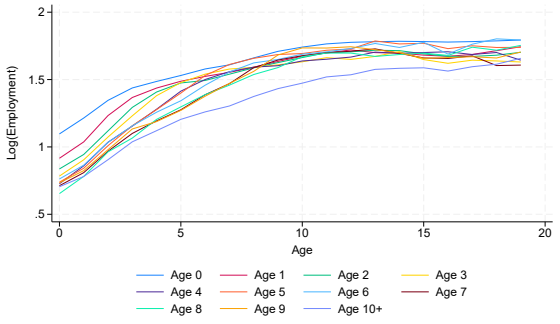
(b) Top 10%

Figure 1: Use of LTD types over the lifecycle

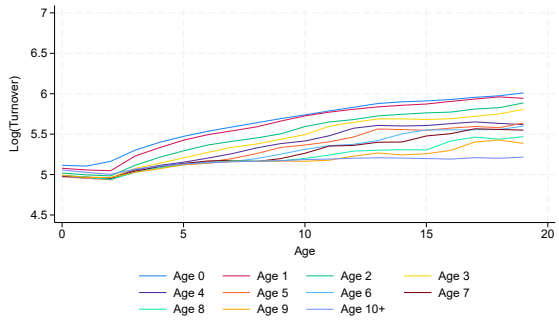
This figure plots the conditional distribution of Long-Term Debt (LTD) types by firm age. The sample is restricted to firms that have accessed the LTD market at least once by the indicated age. Panel 1a presents results for the full universe of incorporated firms. Panel 1b restricts the sample to the top 10% of firms by employment within each age cohort. CF-LTD denotes cash-flow-based long-term debt, while A-LTD denotes asset-based long-term debt. Both indicates that a firm has utilized both debt instruments at some point between incorporation and the specified age. All figures are based on statutory financial filings from Companies House merged with administrative records from the Business Structure Database.



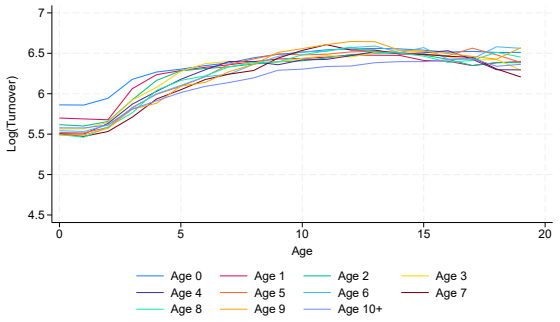
(a) Log(Employment) - CF-LTD



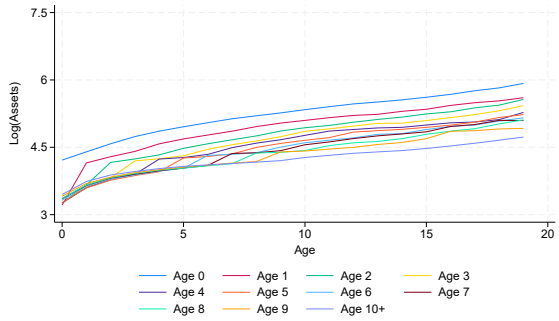
(b) Log(Employment) - A-LTD



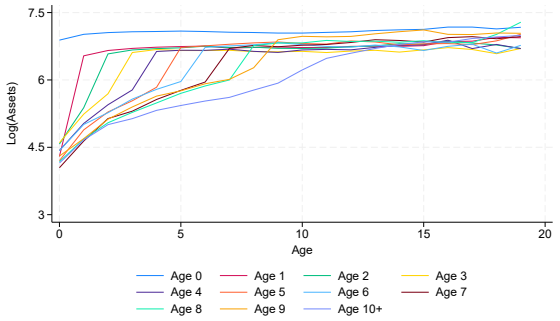
(c) Log(Turnover) - CF-LTD



(d) Log(Turnover) - A-LTD



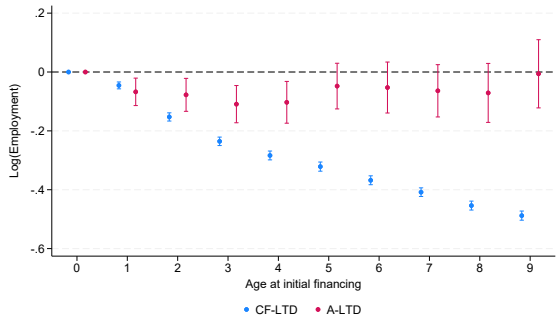
(e) Log(Assets) - CF-LTD



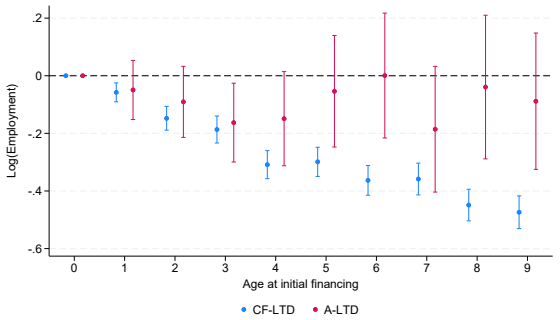
(f) Log(Assets) - A-LTD

Figure 2: Firm dynamics by initial LTD type, age, and age of initial financing

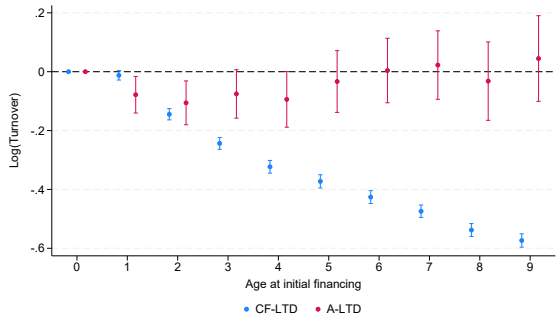
These panels illustrate the evolution of mean log employment, turnover and assets from age 0 through age 19, stratified by the specific age at which a firm first secured long-term debt. Age 10+ includes firms that receive their initial LTD between ages 10 and 19. Panels 2a, 2c and 2e display trajectories for firms whose initial financing was cash-flow-based (CF-LTD), while panels 2b, 2d and 2f display trajectories for those whose initial financing was asset-backed (A-LTD). The figures utilize an unbalanced panel of survivors, where the mean at each age is calculated across all firms in the respective cohort that remain active in the Business Structure Database (BSD). This visualization highlights the persistent quality ladder associated with early-stage cash-flow lending, a pattern that is notably absent in the collateralized debt subsample.



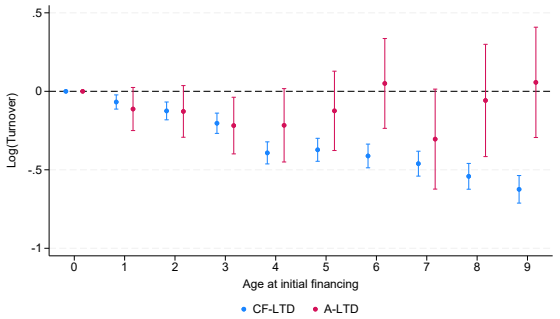
(a) Log(Employment) - Age 10



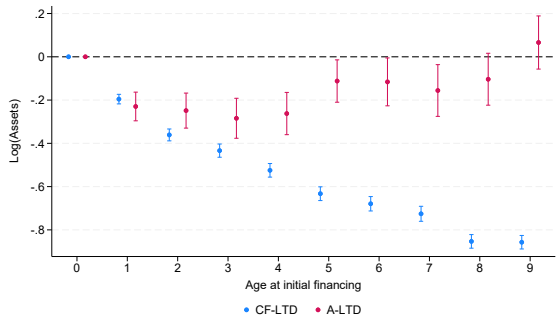
(b) Log(Employment) - Age 19



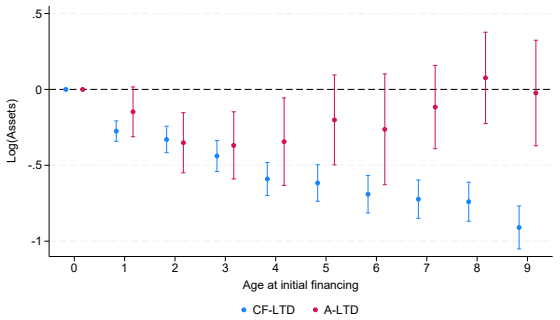
(c) Log(Turnover) - Age 10



(d) Log(Turnover) - Age 19



(e) Log(Assets) - Age 10



(f) Log(Assets) - Age 19

Figure 3: Differences in firm size by age and type of initial LTD financing

These panels illustrate relative differences in mean log employment, turnover and assets at ages 10 and 19 relative to firms financed with same LTD type at age 0. Estimations are based on equation 2. Panels 3a, 3c and 3e display differences at age 10, while panels 3b, 3d and 3f display differences at age 19. Standard errors use a 90 percent significane level. The figures utilize an unbalanced panel of survivors, where the mean at each age is calculated across all firms in the respective cohort that remain active in the Business Structure Database (BSD). This visualization highlights the persistent quality ladder associated with early-stage cash-flow lending, a pattern that is notably absent in the collateralized debt subsample.

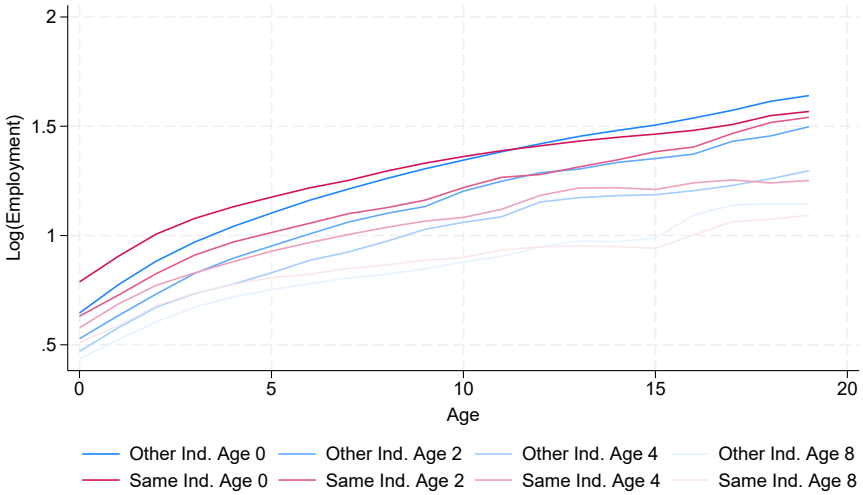


Figure 4: Log(employment) by first use of LT debt and serial entrepreneur experience

This figure plots mean log employment trajectories from Age 0 through Age 19 for serial entrepreneurs, stratified by industry-specific experience and the age of initial long-term debt (LTD) financing. Red lines represent entrepreneurs starting businesses in industries where they possess prior experience, while blue lines denote those entering unfamiliar industries. Separate trajectories are shown for cohorts receiving their first LTD at ages 0, 2, 4, and 8. The visualization demonstrates that, conditional on securing financing at the same age, cross-industry entrants (blue) typically enter at a smaller initial scale but exhibit significantly steeper growth slopes, eventually surpassing their industry-experienced counterparts (red). The figures utilize an unbalanced panel of survivors, where the mean at each age is calculated across all firms in the respective cohort that remain active in the Business Structure Database (BSD).

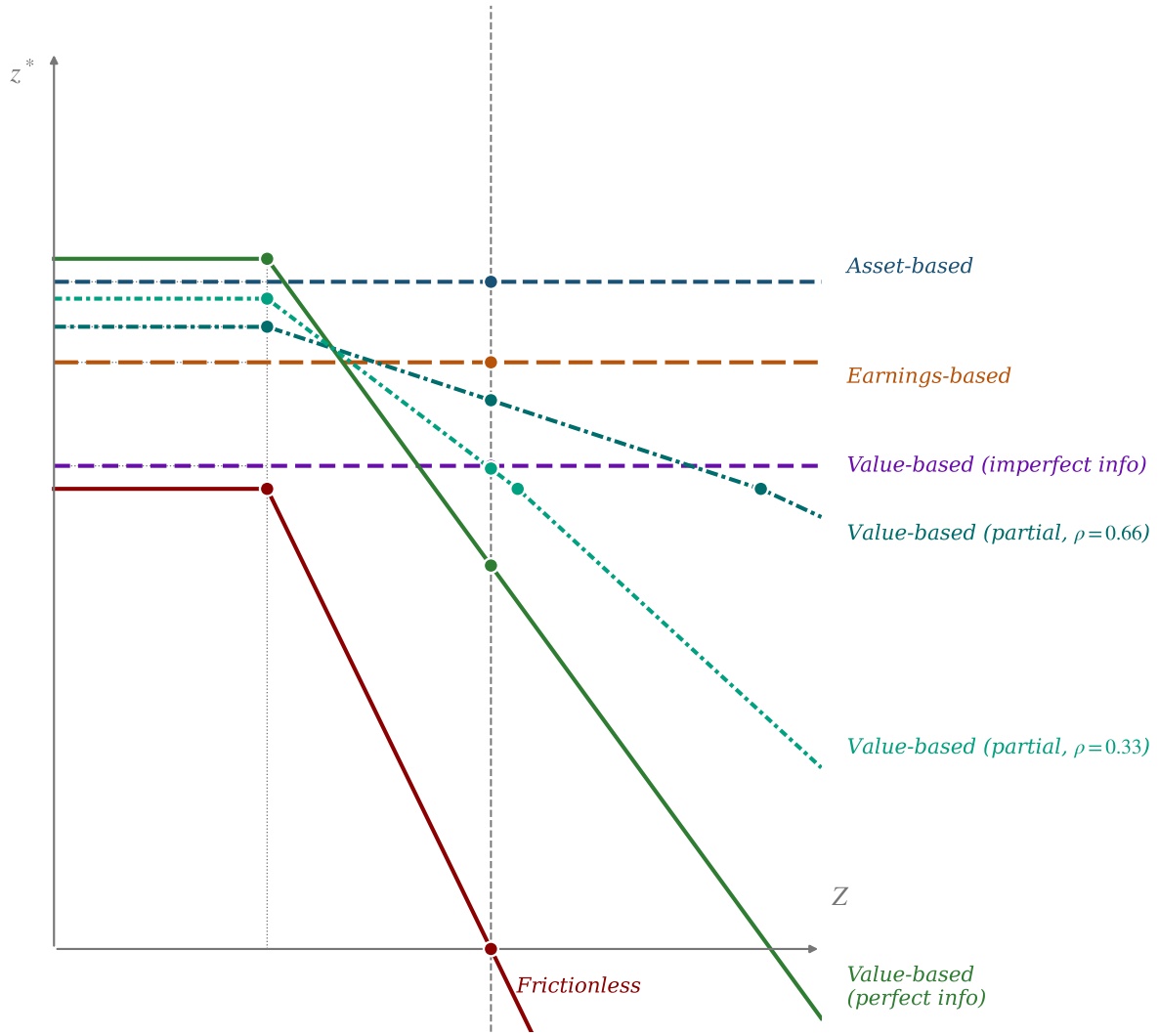


Figure 5: Today's survival threshold tracks future steady-state productivity under valued-based lending but not under asset-based lending.

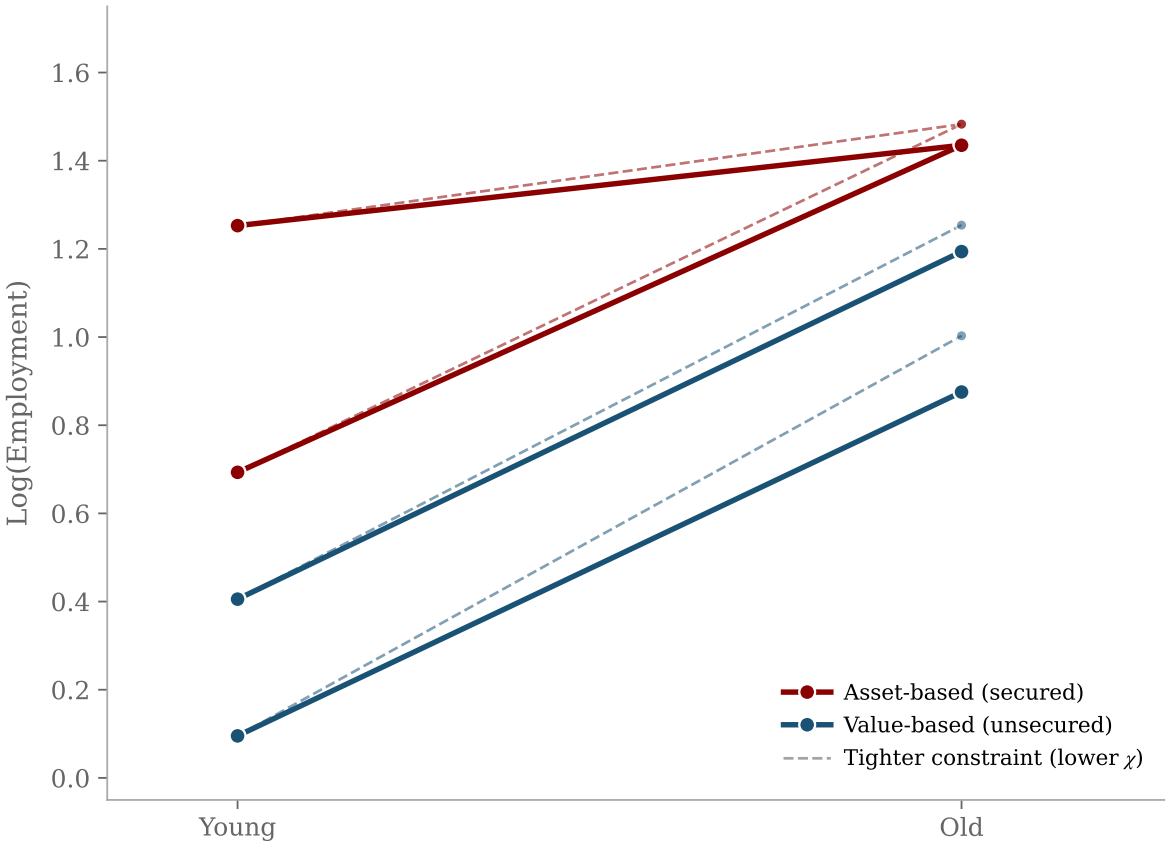


Figure 6: Asset (value) based lending makes firms appear ex-ante homogenous (heterogeneous)

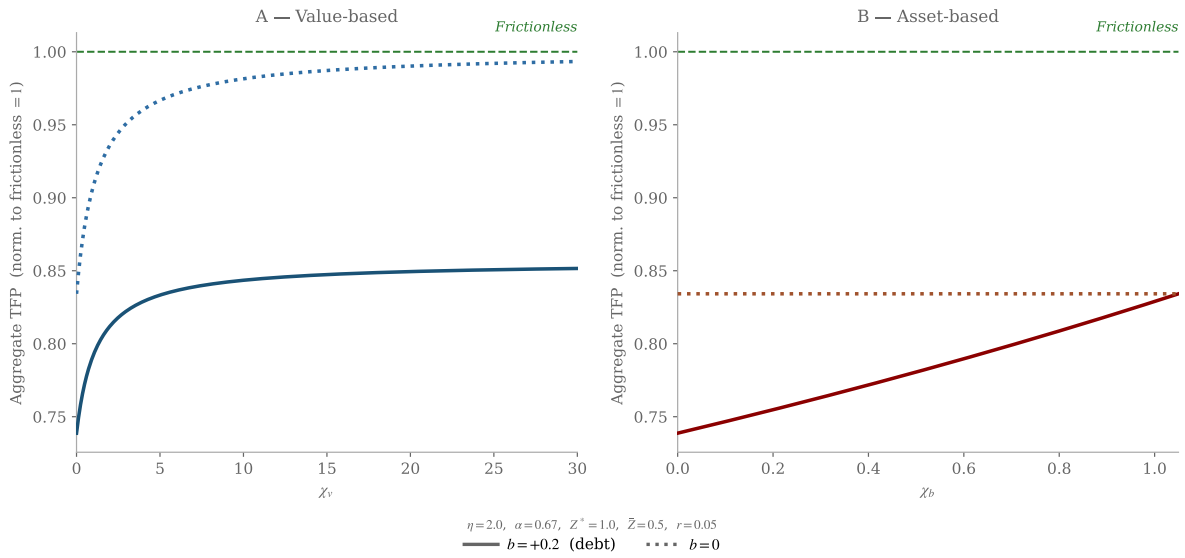


Figure 7: TFP and financial frictions: no collateral limit

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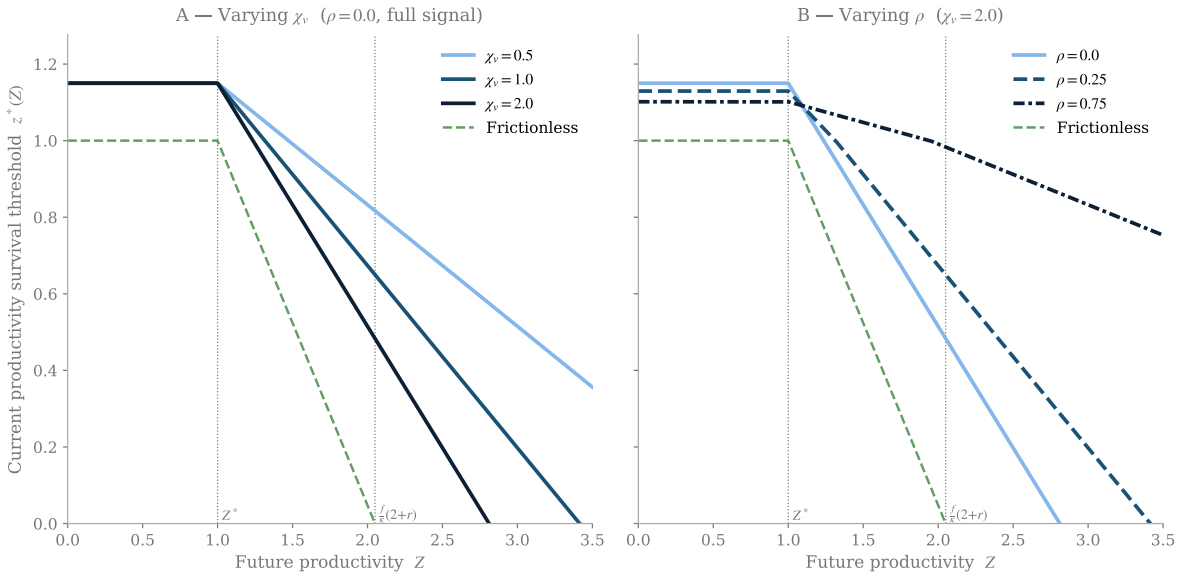


Figure 8: Survival impact of changes in frictions χ and ρ under value-based financing.

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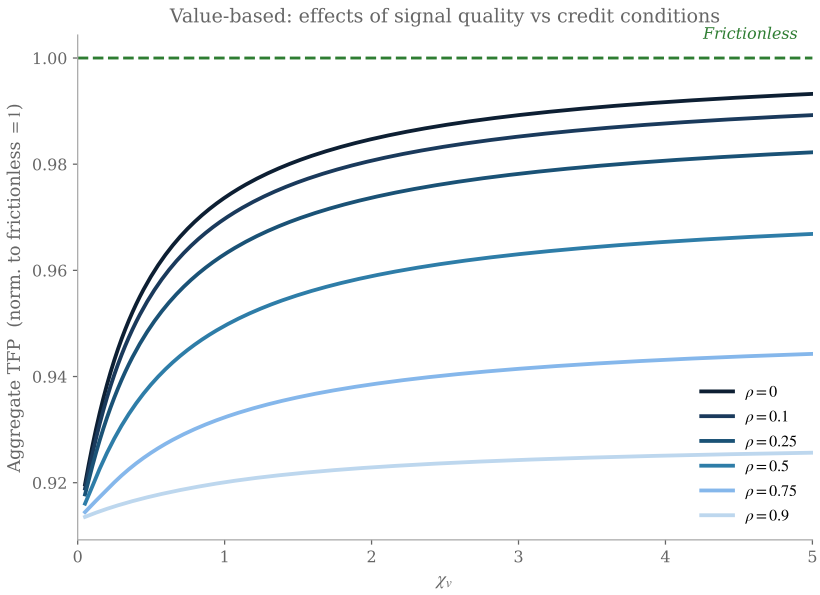


Figure 9: TFP impact of changes in frictions χ and ρ under value-based financing.

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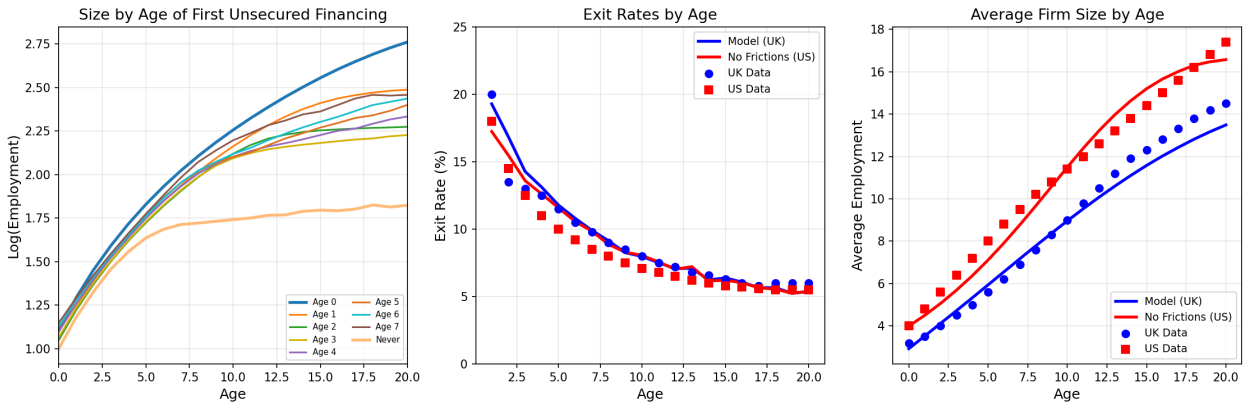


Figure 10: Baseline results with a value based constraint.

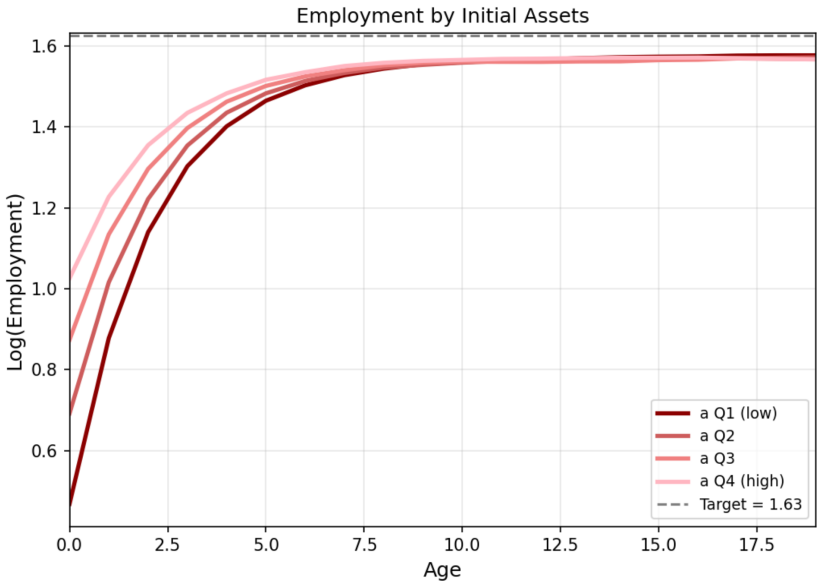


Figure 11: Baseline results With an asset based constraint.

Tables

Table 1: Cohort Summary Statistics: Full, Unsecured, and Secured Samples

		Age 0				Age 10			
Cohort	N	Emp.	LT Debt	Assets	Turn.	Emp.	LT Debt	Assets	Turn.
Panel A: Full Sample									
0	930,824	0.604	2.370	4.384	5.161	1.283	3.498	5.514	5.814
1	275,901	0.527	–	3.275	5.110	1.227	2.985	5.232	5.783
2	151,648	0.469	–	3.322	5.048	1.131	2.824	5.095	5.664
3	104,151	0.436	–	3.316	5.013	1.043	2.769	5.001	5.562
4	75,580	0.414	–	3.308	5.001	0.994	2.540	4.897	5.480
5	57,524	0.399	–	3.306	4.992	0.958	2.372	4.788	5.431
6	42,601	0.398	–	3.359	4.998	0.904	2.193	4.719	5.369
7	31,640	0.390	–	3.379	4.998	0.860	2.063	4.666	5.316
8	24,035	0.375	–	3.386	5.007	0.812	2.068	4.520	5.246
9	18,999	0.361	–	3.441	5.007	0.779	1.994	4.508	5.212
10+	57,810	0.375	–	3.468	5.071	0.754	1.777	4.326	5.216
Never	1,860,996	0.349	–	2.295	4.868	0.504	–	3.711	4.869
Panel B: Firms with initally unsecured LT debt									
0	872,041	0.572	2.157	4.215	5.115	1.233	3.245	5.338	5.738
1	261,518	0.506	–	3.210	5.078	1.188	2.790	5.099	5.726
2	144,083	0.450	–	3.257	5.019	1.081	2.583	4.936	5.594
3	99,533	0.420	–	3.257	4.987	0.998	2.538	4.855	5.494
4	72,528	0.401	–	3.261	4.980	0.950	2.356	4.766	5.415
5	55,397	0.387	–	3.271	4.972	0.912	2.172	4.656	5.366
6	41,155	0.385	–	3.322	4.979	0.865	2.008	4.602	5.312
7	30,571	0.379	–	3.356	4.981	0.825	1.880	4.557	5.264
8	23,266	0.366	–	3.360	4.991	0.779	1.937	4.427	5.200
9	18,396	0.349	–	3.413	4.992	0.745	1.869	4.418	5.164
10+	56,222	0.366	–	3.450	5.057	0.734	1.675	4.274	5.186
Panel C: Firms with initially secured LT debt									
0	58,783	1.096	5.530	6.887	5.862	1.741	5.479	7.044	6.513
1	14,383	0.916	–	4.296	5.699	1.674	4.931	6.722	6.435
2	7,565	0.837	–	4.574	5.617	1.663	4.888	6.701	6.407
3	4,618	0.784	–	4.602	5.566	1.632	4.888	6.637	6.438
4	3,052	0.727	–	4.429	5.505	1.638	4.658	6.668	6.419
5	2,127	0.738	–	4.202	5.521	1.693	4.957	6.811	6.480
6	1,446	0.762	–	4.428	5.544	1.688	4.884	6.786	6.517
7	1,069	0.712	–	4.045	5.501	1.677	4.818	6.774	6.536
8	769	0.654	–	4.181	5.496	1.670	4.815	6.825	6.481
9	603	0.734	–	4.305	5.488	1.735	4.934	6.971	6.558
10+	1,588	0.705	–	4.149	5.578	1.473	4.989	6.223	6.304

This table presents descriptive statistics for the firm universe at two distinct lifecycle milestones: inception (Age 0) and maturity (Age 10). The data is partitioned into three panels: Panel A includes the full sample of firms; Panel B is restricted to firms whose initial long-term debt was cash-flow-based (CF-LTD); and Panel C is restricted to firms whose initial long-term debt was asset-based (A-LTD). N denotes the total number of unique firms in each subsample. All other variables—including employment, long-term debt, total assets, and turnover—are reported as mean log-transformed values. The mean at each age is calculated across all firms in the respective cohort that remain active in the Business Structure Database (BSD).

Table 2: Predictive Power of Initial Debt and Startup Characteristics for Long-run Scale

Dependent Variable:	Log Employment (Age 10)			Log Employment (Age 19)		
	(1)	(2)	(3)	(4)	(5)	(6)
Initial Long-Term Debt	0.4749***	0.1949***	0.2839***	0.4993***	0.1857***	0.2727***
	(0.0034)	(0.0030)	(0.0033)	(0.0095)	(0.0091)	(0.0097)
Log Employment (Age 0)		0.5358***			0.4503***	
		(0.0028)			(0.0079)	
Log Turnover (Age 0)		0.0593***			0.0959***	
		(0.0022)			(0.0062)	
Log Total Assets (Age 0)		0.0499***	0.1286***		0.0459***	0.1307***
		(0.0008)	(0.0100)		(0.0023)	(0.0027)
Log Productivity (Age 0)			-0.0590***			-0.0297***
			(0.0025)			(0.0068)
N	560,412	560,412	560,412	84,504	84,504	84,504
R-squared	0.0389	0.2768	0.0976	0.0347	0.2166	0.0822

This table reports OLS regressions based on equation 1. Dependent variables are employment at Age 10 (Columns 1–3) and Age 19 (Columns 4–6). Columns 1 and 4 present the baseline relationship; Columns 2 and 5 include full initial scale controls; Columns 3 and 6 isolate the predictive power of debt relative to initial assets and productivity. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Long-run Firm Outcomes by Age of Initial Long-Term Debt

	Log(Employment)		Log(Turnover)		Log(Assets)	
	(1) CF-LTD	(2) A-LTD	(3) CF-LTD	(4) A-LTD	(5) CF-LTD	(6) A-LTD
Panel A: Outcomes at Age 10						
Age of First Debt = 1	-0.0455***	-0.0674***	-0.0124	-0.0783**	-0.1956***	-0.2296***
	(0.0060)	(0.0238)	(0.0081)	(0.0317)	(0.0113)	(0.0338)
Age of First Debt = 2	-0.1527***	-0.0776***	-0.1445***	-0.1058***	-0.3611***	-0.2487***
	(0.0071)	(0.0286)	(0.0098)	(0.0380)	(0.0140)	(0.0413)
Age of First Debt = 3	-0.2355***	-0.1092***	-0.2436***	-0.0754*	-0.4338***	-0.2842***
	(0.0073)	(0.0323)	(0.0103)	(0.0420)	(0.0156)	(0.0471)
Age of First Debt = 4	-0.2835***	-0.1029***	-0.3231***	-0.0941*	-0.5247***	-0.2623***
	(0.0077)	(0.0362)	(0.0110)	(0.0482)	(0.0161)	(0.0498)
Age of First Debt = 5	-0.3214***	-0.0478	-0.3725***	-0.0334	-0.6328***	-0.1121**
	(0.0079)	(0.0396)	(0.0114)	(0.0535)	(0.0162)	(0.0499)
Age of First Debt = 6	-0.3679***	-0.0527	-0.4260***	0.0040	-0.6793***	-0.1160**
	(0.0077)	(0.0442)	(0.0111)	(0.0559)	(0.0170)	(0.0565)
Age of First Debt = 7	-0.4083***	-0.0639	-0.4742***	0.0226	-0.7257***	-0.1558**
	(0.0075)	(0.0453)	(0.0108)	(0.0593)	(0.0177)	(0.0610)
Age of First Debt = 8	-0.4538***	-0.0710	-0.5379***	-0.0320	-0.8532***	-0.1037*
	(0.0077)	(0.0511)	(0.0112)	(0.0680)	(0.0160)	(0.0612)
Age of First Debt = 9	-0.4880***	-0.0061	-0.5735***	0.0448	-0.8571***	0.0661
	(0.0079)	(0.0591)	(0.0116)	(0.0743)	(0.0159)	(0.0627)
N	390,246	33,283	389,534	33,142	299,460	27,198
R-squared	0.0216	0.0008	0.0161	0.0005	0.0235	0.0040
Panel B: Outcomes at Age 19						
Age of First Debt = 1	-0.0577***	-0.0494	-0.0680***	-0.1128	-0.2748***	-0.1477*
	(0.0167)	(0.0524)	(0.0231)	(0.0700)	(0.0343)	(0.0837)
Age of First Debt = 2	-0.1477***	-0.0907	-0.1249***	-0.1281	-0.3300***	-0.3516***
	(0.0210)	(0.0629)	(0.0290)	(0.0840)	(0.0445)	(0.1011)
Age of First Debt = 3	-0.1867***	-0.1628**	-0.2035***	-0.2182**	-0.4390***	-0.3690***
	(0.0239)	(0.0697)	(0.0329)	(0.0920)	(0.0520)	(0.1129)
Age of First Debt = 4	-0.3087***	-0.1491*	-0.3923***	-0.2165*	-0.5901***	-0.3446**
	(0.0248)	(0.0834)	(0.0358)	(0.1192)	(0.0554)	(0.1470)
Age of First Debt = 5	-0.2989***	-0.0539	-0.3726***	-0.1244	-0.6168***	-0.2012
	(0.0258)	(0.0987)	(0.0373)	(0.1289)	(0.0614)	(0.1511)
Age of First Debt = 6	-0.3631***	0.0006	-0.4118***	0.0502	-0.6904***	-0.2630
	(0.0263)	(0.1105)	(0.0385)	(0.1460)	(0.0631)	(0.1862)
Age of First Debt = 7	-0.3585***	-0.1857*	-0.4609***	-0.3044*	-0.7231***	-0.1165
	(0.0281)	(0.1113)	(0.0405)	(0.1625)	(0.0644)	(0.1399)
Age of First Debt = 8	-0.4489***	-0.0393	-0.5415***	-0.0582	-0.7401***	0.0759
	(0.0280)	(0.1272)	(0.0419)	(0.1824)	(0.0657)	(0.1535)
Age of First Debt = 9	-0.4738***	-0.0885	-0.6243***	0.0572	-0.9096***	-0.0237
	(0.0289)	(0.1207)	(0.0448)	(0.1792)	(0.0724)	(0.1774)
N	55,671	8,089	55,539	8,058	30,531	4,402
R-squared	0.0129	0.0013	0.0105	0.0017	0.0180	0.0059

This table reports OLS regressions based on equation 2. Dependent variables are log employment, log turnover, and log total assets measured at firm Age 10 (Panel A) and Age 19 (Panel B). The independent variables are dummy indicators for the age at which a firm first secured long-term debt, with Age 0 (inception) as the omitted reference category. Odd-numbered columns report results for the CF-LTD sample, while even-numbered columns report results for the A-LTD sample. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix

A Theory Appendix

A.1 Proof of Lemma 1

Proof. See Appendix.

$$\kappa z - f + \frac{1}{1+r}\mathbb{E}_{Z|z}\max\left\{\kappa Z - f, 0\right\} \geq 0$$

Only productive enough firms will survive tomorrow if

$$Z > Z^* \equiv \frac{f}{\kappa}$$

$$\mathbb{E}_{Z|z}\max\left\{\kappa Z - f, 0\right\} = \Pr\left(Z \geq Z^*\right)\mathbb{E}_{Z|Z\geq Z^*,z}\left(\kappa Z - f\right)$$

$$\kappa z - f\left(1 + \frac{\Pr\left(Z \geq Z^*\right)}{1+r}\right) + \frac{Pr\left(Z \geq Z^*\right)}{1+r}\mathbb{E}_{Z|Z\geq Z^*,z}\kappa\left(Z\right) \geq 0$$

$$z + \frac{Pr\left(Z \geq Z^*\right)}{1+r}\mathbb{E}_{Z|Z\geq Z^*,z}\left(Z\right) \geq \frac{f}{\kappa}\left(1 + \frac{\Pr\left(Z \geq Z^*\right)}{1+r}\right)$$

Hence their threshold

$$z \geq z^*\left(z, Z\right) = \frac{f}{\kappa}\left(1 + \frac{Pr\left(Z \geq Z^*\right)}{1+r}\right) - \frac{Pr\left(Z \geq Z^*\right)}{1+r}\mathbb{E}_{Z|Z\geq \frac{f}{\kappa},z}Z$$

Thus, future superstars Z will find it easier to survive today (will have a lower threshold $z^*\left(z, Z\right)$).

If Z is unknown to the firm we have that $Z \sim G(Z)$ is Pareto, this simplifies to:

$$\Pr\left(Z \geq Z^*\right) = \left(\frac{Z}{Z^*}\right)^{\zeta} = \left(\frac{\kappa \underline{Z}}{f}\right)^{\zeta}$$

$$\mathbb{E}\left[Z \mid Z \geq Z^*\right] = \frac{\zeta}{\zeta - 1}Z^* = \frac{\zeta}{\zeta - 1}\frac{f}{\kappa}$$

$$
\begin{aligned}
z^*(z,Z) &= \frac{f}{\kappa}\left(1+\frac{\Pr\left(Z\geq Z^*\right)}{1+r}\right)-\frac{\Pr\left(Z\geq Z^*\right)}{1+r}\cdot\frac{\zeta}{\zeta-1}\frac{f}{\kappa}\\
&= \frac{f}{\kappa}\left[1+\frac{\Pr\left(Z\geq Z^*\right)}{1+r}\left(1-\frac{\zeta}{\zeta-1}\right)\right]\\
&= \frac{f}{\kappa}\left[1-\frac{\Pr\left(Z\geq Z^*\right)}{(\zeta-1)(1+r)}\right]\\
&= \frac{f}{\kappa}\left[1-\frac{\left(\frac{\kappa Z}{f}\right)^{\zeta}}{(\zeta-1)(1+r)}\right]
\end{aligned}
$$

However, if Z is known to the firm,

$$
\begin{aligned}
\mathbb{E}\left[Z \mid Z\geq Z^*, z\right] &= Z\\
\Pr\left(Z\geq Z^*\right) &= \mathbf{1}\left[Z\geq Z^*\right]
\end{aligned}
$$

Hence, the threshold becomes Z dependent

$$
z^*(Z) = \frac{f}{\kappa}\left(1+\frac{\mathbf{1}\left[Z\geq Z^*\right]}{1+r}\right)-\frac{\mathbf{1}\left[Z\geq Z^*\right]}{1+r}Z
$$

Thus, we have that:

$$
z^*\left(Z\right) = \begin{cases} \frac{f}{\kappa(w)} & \text{if } Z < Z^* \\ \frac{f}{\kappa(w)}\cdot\frac{2+r}{1+r}-\frac{Z}{1+r} & \text{if } Z\geq Z^* \end{cases}
$$

Q.E.D.

A.2 Proof of Lemma 2

Proof of Lemma 2. Plug in:

$$
v\left(z,Z,b\right) = \max_{d,b'}\left\{\pi(z)-b+\frac{b'}{1+r}+\frac{1}{1+r}\mathbb{E}_{Z|z}\left[\max\left\{\pi(Z)-b',0\right\}\right],-b\right\}
$$

If $d>0$ is optimal because the firm has very high z, the firm is not financially constrained.

If $d=0$ then, firms that have negative cashflows will borrow more even without existing debt.

$$
b' = (1+r)\left(b-\pi(z)\right)
$$

Firms will be able to borrow up to:

$$
(1+r)\left(b-\pi(z)\right)\leq\chi b
$$

Then, with the borrowing constraint, the following firms will not be able to survive

and will exit.

The survival threshold of future superstars Z is independent of Z and crucially now depends on b.

$$(1+r)(b-(\kappa z-f))\leq \chi b$$
$$(1+r)b-(1+r)\kappa z+(1+r)f\leq \chi b$$
$$(1+r-\chi)b+(1+r)f\leq (1+r)\kappa z$$
$$z\geq \frac{f}{\kappa}+\left(1-\frac{\chi}{1+r}\right)\frac{b}{\kappa}$$

$$z\geq z_b\left(b\right)=\frac{f}{\kappa}+\left(1-\bar{\Gamma}_b\right)\frac{b}{\kappa},\quad \text{s.t.}\quad \bar{\Gamma}_b=\left(1-\frac{\chi_b}{1+r}\right)$$

The main insight is that the asset-based constraint kills forward-looking selection i.e. regardless of future productivity Z.

A.3 Proof of Lemma 3

Proof of Lemma 3.

$$v\left(z,Z,b\right)=\max_{d,b'}\left\{\pi(z)-b+\frac{b'}{1+r}+\frac{1}{1+r}\mathbb{E}_{Z|z}v(Z,b'),-b'\right\}$$

If dividends bind, the earnings based constraint is slack (and the firm survives) as long as:

$$\left(1+r\right)\left(b-\pi(z)\right)=b'\leq \chi_\pi\pi(z)$$

Hence,

$$b\leq \frac{1+r+\chi_\pi}{(1+r)}\pi(z)$$

Thus, an earnings based constraint is essentially isomorphic to an asset based one with a different constant.

$$z\geq z_\pi(b)=\frac{f}{\kappa}+\left(\frac{1+r}{1+r+\chi_\pi}\right)\frac{b}{\kappa}$$

$$z\geq z_\pi(b)=\frac{f}{\kappa}+\bar{\Gamma}_\pi\frac{b}{\kappa},\quad \text{s.t.}\quad \bar{\Gamma}_\pi=\left(\frac{1+r}{1+r+\chi_\pi}\right)$$

QED.

A.4 Proof of Proposition 1 and Corollary 1

Proof of Proposition 1 & Corollary 1.

Perfect information.

$$\mathbb{E}_{Z|z}v(Z,b')=\max\left\{\pi(Z),0\right\}-b'$$

$$b' \leq \chi_v \left[\max\left\{\pi(Z), 0\right\} - b'\right]$$

$$b' \leq \frac{\chi_v}{1+\chi_v} \max\left\{\kappa Z - f, 0\right\} = \max\left\{\frac{\chi_v}{1+\chi_v}\left(\kappa Z - f\right), 0\right\}$$

Whenever $d = 0$, the constraint will be slack if

$$b' = (1+r)\left(b - \pi(z)\right) = (1+r)\left(b + f - \kappa z\right) \leq \frac{\chi_v}{1+\chi_v} \max\left\{\kappa Z - f, 0\right\}$$

Or

$$z \geq z_v\left(b, Z\right) = \frac{b}{\kappa} + \frac{f}{\kappa} - \frac{1}{(1+r)} \frac{\chi_v}{1+\chi_v} \max\left\{Z - \frac{f}{\kappa}, 0\right\}$$

Imperfect information.
In the general case when Z is not perfectly known, we have:

$$b' \leq \chi_v \mathbb{E}_{Z|z} \max\left\{\pi(Z) - b', -b'\right\}$$

Regardless, if the firm has $d = 0$, then again:

$$b' = (1+r)\left(b - \pi(z)\right)$$

if on top of that

$$b' \leq \frac{\chi_v}{1+\chi_v} \mathbb{E}_{Z|z} \max\left\{\pi(Z), 0\right\}$$

Thus,

$$b' = (1+r)\left(b - \pi(z)\right) \leq \frac{\chi_v}{1+\chi_v} \mathbb{E}_{Z|z} \max\left\{\pi(Z), 0\right\}$$

$$b' = (1+r)\left(b - \kappa z\right) \leq \frac{\chi_v}{1+\chi_v} \mathbb{E}_{Z|z} \max\left\{\pi(Z), 0\right\}$$

$$z \geq z_v(z, Z, b) = \frac{b}{\kappa} + \frac{f}{\kappa} - \frac{\chi_v}{1+\chi_v} \frac{1}{(1+r)} \frac{\mathbb{E}_{Z|z} \max\left\{\pi(Z), 0\right\}}{\kappa}$$

Inherently the term is the expected value of a call option with uncertain future price Z and strike price $\frac{f}{\kappa}$.

$$\frac{\mathbb{E}_{Z|z} \max\left\{\pi(Z), 0\right\}}{\kappa} = \mathbb{E}_{Z|z} \max\left\{Z - \frac{f}{\kappa}, 0\right\}$$

Note that as before we have $Z^* = f/\kappa(w)$ and

$$\Pr\left(Z \geq Z^*\right) = \left(\frac{Z}{Z^*}\right)^{\zeta} = \left(\frac{\kappa Z}{f}\right)^{\zeta}$$

$$\mathbb{E}\left[Z \mid Z \geq Z^*\right] = \frac{\zeta}{\zeta - 1} Z^* = \frac{\zeta}{\zeta - 1} \frac{f}{\kappa}$$

$$Pr\left(Z \geq Z^*\right) \mathbb{E}\left[Z \mid Z \geq Z^*\right] = \frac{\zeta}{\zeta - 1} \left(\underline{Z}\right)^{\zeta} \left(Z^*\right)^{1-\zeta}$$

$$\mathbb{E}_{Z|z} \max\left\{\pi(Z), 0\right\} = \kappa \mathbb{P}\left[Z \geq Z^*\right] \mathbb{E}\left[Z \mid Z \geq Z^*\right] - \mathbb{P}\left[Z \geq Z^*\right] f$$

$$z \geq z_v(z, Z, b) = \frac{b}{\kappa} + \frac{f}{\kappa} + \frac{\chi_v}{1+\chi_v} \frac{\mathbb{P}\left[Z \geq Z^*\right]}{(1+r)} \frac{f}{\kappa} - \frac{\chi_v}{1+\chi_v} \frac{Pr\left(Z \geq Z^*\right) \mathbb{E}\left[Z \mid Z \geq Z^*\right]}{(1+r)}$$

$$z \geq z_v(z, b) = \frac{b}{\kappa} + \frac{f}{\kappa} + \frac{\chi_v}{1+\chi_v} \frac{\left(\underline{Z}\right)^{\zeta} \left(\frac{f}{\kappa}\right)^{1-\zeta}}{(1+r)} - \frac{\chi_v}{1+\chi_v} \frac{\zeta}{\zeta - 1} \frac{\left(\underline{Z}\right)^{\zeta} \left(\frac{f}{\kappa}\right)^{1-\zeta}}{(1+r)}$$

$$z \geq z_v(b) = \frac{b}{\kappa} + \left(1 + \frac{\chi_v}{1+\chi_v} \frac{1}{(1+r)} \frac{\left(\underline{Z}\right)^{\zeta} \left(\frac{f}{\kappa}\right)^{-\zeta}}{\zeta - 1}\right) \frac{f}{\kappa}$$

$$z \geq z_v(b) = \frac{b}{\kappa} + \bar{\Gamma}_v \frac{f}{\kappa}$$

$$\bar{\Gamma}_v = \left(1 + \frac{\chi_v}{1+\chi_v} \frac{1}{(1+r)} \frac{\left(\underline{Z}\right)^{\zeta} \left(\frac{f}{\kappa}\right)^{-\zeta}}{\zeta - 1}\right)$$

Consider an imperfect signal for a firms' Z.

$$b' \leq \frac{\chi_v}{1+\chi_v} \mathbb{E}^*_{Z|z} \max\left\{\pi(Z), 0\right\}$$

$$b' \leq \frac{\chi_v}{1+\chi_v} \left(\mathbb{P}^*_{Z|z} \kappa \mathbb{E}_{Z|z} Z - \mathbb{P}^*_{Z|z} f\right)$$

$$b' \leq \frac{\chi_v}{1+\chi_v} \left(\mathbb{P}^*\left(z, Z, b\right) \kappa \mathbb{E}^*\left(z, Z, b\right) - \mathbb{P}^*\left(z, Z, b\right) f\right)$$

Hence

$$b' = (1+r)\left(b + f - \kappa z\right) \leq \frac{\chi_v}{1+\chi_v} \left(\mathbb{P}^*\left(z, Z, b\right) \kappa \mathbb{E}^*\left(z, Z, b\right) - \mathbb{P}^*\left(z, Z, b\right) f\right)$$

Thus, as long as $z \geq z^i_v(z, Z, b)$ we have:

$$z \geq \frac{b}{\kappa} + \frac{f}{\kappa} + \frac{\chi_v}{1+\chi_v} \frac{\mathbb{P}^*\left(z, Z, b\right)}{(1+r)} \frac{f}{\kappa} - \frac{\chi_v}{1+\chi_v} \frac{1}{(1+r)} \mathbb{P}^*\left(z, Z, b\right) \mathbb{E}^*\left(z, Z, b\right)$$

where z_v is implicitly defined by:

$$z_v = \frac{b}{\kappa} + \left(1 + \frac{\chi_v}{1+\chi_v} \frac{\mathbb{P}^*\left(z_v, Z, b\right)}{1+r}\right) \frac{f}{\kappa} - \frac{\chi_v}{1+\chi_v} \frac{\mathbb{P}^*\left(z_v, Z, b\right) \mathbb{E}^*\left(z_v, Z, b\right)}{1+r}$$

Tractable example.

With probability $1-\rho$ the lender is right and they get Z. With probability ρ today was the right one z.

$$z'|z,Z = \begin{cases} z & \text{with probability } \rho \\ Z & \text{with probability } 1-\rho \end{cases}$$

Hence, the expected productivity of a firms is like an AR(1) Markov process that has persistence ρ of past z with a drift related to the long-run Z.

$$\mathbb{E}\left(z'|z,Z\right) = (1-\rho)\,Z + \rho z$$

Intuitively, ρ captures the degree at which lenders (and the firm) look at today vs tomorrow when trying to infer where the firm is going to be in their steady state.

Hence, the firm's problem:

$$v\left(z,Z,b\right) = \max_{d,b'}\left\{d + \frac{1}{1+r}\mathbb{E}_{z'|z,Z}\max\left\{\pi(z') - b', -b'\right\}, -b\right\}$$

$$d = \pi(z) - b + \frac{b'}{1+r} \geq 0$$

$$b' \leq \chi_v \mathbb{E}_{z'|z,Z}\max\left\{\pi(z') - b', -b'\right\}$$

$$b' \leq \frac{\chi_v}{1+\chi_v}\mathbb{E}_{z'|z,Z}\max\left\{\pi(z'), 0\right\}$$

Thus, the firms' value function:

$$v\left(z,Z,b\right) = \max_{d,b'}\left\{d + \frac{1}{1+r}\left[\rho\max\left\{\pi(z),0\right\} + (1-\rho)\max\left\{\pi(Z),0\right\}\right] - \frac{b'}{1+r}, -b\right\}$$

Given the uncertainty about whether the firms signal about Z is the right one or whether they're going to remain at z, we have:

$$b' \leq \frac{1}{1+\frac{1}{\chi_v}}\left[\rho\max\left\{\pi(z),0\right\} + (1-\rho)\max\left\{\pi(Z),0\right\}\right]$$

$$b' \leq \frac{1}{1+\frac{1}{\chi_v}}\left[\rho\max\left\{\kappa z - f,0\right\} + (1-\rho)\max\left\{\kappa Z - f,0\right\}\right]$$

Hence

$$b' = (1+r)\left(b + f - \kappa z\right) \leq \frac{1}{1+\frac{1}{\chi_v}}\left[\rho\max\left\{\kappa z - f,0\right\} + (1-\rho)\max\left\{\kappa Z - f,0\right\}\right]$$

Thus, as long as $z \geq z_v^i(z,Z,b)$ we have:

$$(b+f-\kappa z) \leq \frac{1}{1+r}\frac{1}{1+\frac{1}{\chi_v}}\left[\rho \max\left\{\kappa z - f, 0\right\} + (1-\rho)\max\left\{\kappa Z - f, 0\right\}\right]$$

$$\kappa z - f \geq b - \frac{1}{1+r}\frac{1}{1+\frac{1}{\chi_v}}\left[\rho \max\left\{\kappa z - f, 0\right\} + (1-\rho)\max\left\{\kappa Z - f, 0\right\}\right]$$

$$z \geq \frac{b}{\kappa} + \frac{f}{\kappa} - \frac{1}{(1+r)}\frac{1}{1+\frac{1}{\chi_v}}\left[\rho \max\left\{z - \frac{f}{\kappa}, 0\right\} + (1-\rho)\max\left\{Z - \frac{f}{\kappa}, 0\right\}\right]$$

Thus, at the threshold of current productivity $z = z_v = z_v(b, Z)$ for which the firm finds it profitable to survive is:

$$z_v = \frac{f}{\kappa} + \frac{b}{\kappa} - \frac{1}{(1+r)}\frac{1}{1+\frac{1}{\chi_v}}\left[\rho \max\left\{z_v - \frac{f}{\kappa}, 0\right\} + (1-\rho)\max\left\{Z - \frac{f}{\kappa}, 0\right\}\right]$$

Note that $z_v - \frac{f}{\kappa} > 0$ ("static" active region)

$$\kappa z - f \geq b - \frac{1}{1+r}\frac{1}{1+\frac{1}{\chi_v}}\left[\rho\left(\kappa z - f\right) + (1-\rho)\max\left\{\kappa Z - f, 0\right\}\right]$$

$$(\kappa z - f)\left(1 + \rho\frac{1}{1+r}\frac{1}{1+\frac{1}{\chi_v}}\right) \geq b - \frac{1}{1+r}\frac{(1-\rho)}{1+\frac{1}{\chi_v}}\left[\max\left\{\kappa Z - f, 0\right\}\right]$$

$$z \geq \frac{f}{\kappa} + \frac{1}{\left(1+\rho\frac{1}{1+r}\frac{1}{1+\frac{1}{\chi_v}}\right)}\frac{b}{\kappa} - \frac{(1-\rho)\frac{1}{1+r}\frac{1}{1+\frac{1}{\chi_v}}}{\left(1+\rho\frac{1}{1+r}\frac{1}{1+\frac{1}{\chi_v}}\right)}\left[\max\left\{Z - \frac{f}{\kappa}, 0\right\}\right]$$

$$\frac{b}{\kappa} \geq \frac{1}{(1+r)}\frac{1}{1+\frac{1}{\chi_v}}\left[\rho \max\left\{z_v - \frac{f}{\kappa}, 0\right\} + (1-\rho)\max\left\{Z - \frac{f}{\kappa}, 0\right\}\right]$$

This happens as long as b is such that the firms' assets are such that:

$$(1+r)\,b \geq \frac{\chi_v}{1+\chi_v}\left[\rho \max\left\{\kappa z_v - f, 0\right\} + (1-\rho)\max\left\{\kappa Z - f, 0\right\}\right]$$

Hence, in this case

$$z_v - \frac{f}{\kappa} = \frac{b}{\kappa} - \frac{1}{(1+r)}\frac{1}{1+\frac{1}{\chi_v}}\left[\rho\left(z_v - \frac{f}{\kappa}\right) + (1-\rho)\max\left\{Z - \frac{f}{\kappa}, 0\right\}\right]$$

$$\left(z_v - \frac{f}{\kappa}\right)\left[1+\rho\frac{1}{(1+r)}\frac{1}{1+\frac{1}{\chi_v}}\right] = \frac{b}{\kappa} - \frac{1}{(1+r)}\frac{(1-\rho)}{1+\frac{1}{\chi_v}}\left[\max\left\{Z-\frac{f}{\kappa},0\right\}\right]$$

$$z_v = z_v(b,Z) = \frac{f}{\kappa} + \left[1+\rho\frac{1}{(1+r)}\frac{1}{1+\frac{1}{\chi_v}}\right]^{-1}\left[\frac{b}{\kappa} - \frac{1}{(1+r)}\frac{(1-\rho)}{1+\frac{1}{\chi_v}}\left[\max\left\{Z-\frac{f}{\kappa},0\right\}\right]\right]$$

$$z \geq \frac{f}{\kappa} + \frac{1}{\left(1+\rho\frac{1}{1+r}\frac{1}{1+\frac{1}{\chi_v}}\right)}\frac{b}{\kappa} - \frac{(1-\rho)\frac{1}{1+r}\frac{1}{1+\frac{1}{\chi_v}}}{\left(1+\rho\frac{1}{1+r}\frac{1}{1+\frac{1}{\chi_v}}\right)}\left[\max\left\{Z-\frac{f}{\kappa},0\right\}\right]$$

Otherwise, we have that if at the threshold: $z_v - \frac{f}{\kappa} \leq 0$ then

$$z_v = \frac{f}{\kappa} + \frac{b}{\kappa} - \frac{1}{(1+r)}\frac{(1-\rho)}{1+\frac{1}{\chi_v}}\max\left\{Z-\frac{f}{\kappa},0\right\}$$

Hence, to summarize, we have that, the general threshold rule simplifies to:

$$z_v = \frac{f}{\kappa} + \left[1+\rho\frac{1}{(1+r)}\frac{\chi_v}{1+\chi_v}\right]^{-\mathbf{1}\left\{z_v-\frac{f}{\kappa}\geq 0\right\}}\left[\frac{b}{\kappa} - \frac{(1-\rho)}{(1+r)}\frac{\chi_v}{1+\chi_v}\max\left\{Z-\frac{f}{\kappa},0\right\}\right]$$

When $\rho \to 0$ we get the perfect information case:

$$z \geq z_v(b,Z) = \frac{b}{\kappa} + \frac{f}{\kappa} - \frac{1}{(1+r)}\frac{\chi_v}{1+\chi_v}\max\left\{Z-\frac{f}{\kappa},0\right\}$$

While with $\rho \to 1$ we get that $z = Z$ constant and we can drop the option value altogether and we recover:

$$z_v = \frac{f}{\kappa} + \left(1+\left[1+\frac{1}{(1+r)}\frac{\chi_v}{1+\chi_v}\right]^{-\mathbf{1}\left\{z_v-\frac{f}{\kappa}\geq 0\right\}}\right)\frac{b}{\kappa}$$

Note that this case is one where the earnings-based constraint is recovered, i.e.

$$(1+r)(b+f-\kappa z) = b' \leq \frac{1}{1+\frac{1}{\chi_v}}\left[\max\left\{\kappa z - f, 0\right\}\right]$$

In summary, there are three key regions:

- When $Z \leq f/\kappa$, there's no possible future since the firm will not continue. z_v is flat in Z.
- When $Z > f/\kappa$, the promise of future cashflows help the firm borrow today. z_v falls with Z.

- Eventually, $z_v \leq f/\kappa$. This means that the firm will survive even if their current cashflows are negative.

$$z_v(Z,b) = \begin{cases} \frac{f}{\kappa} + \left[1 + \rho\frac{1}{1+r}\frac{\chi_v}{1+\chi_v}\right]^{-1}\frac{b}{\kappa}, & \text{if } Z \leq \frac{f}{\kappa}, \\ \frac{f}{\kappa} + \left[1 + \rho\frac{1}{1+r}\frac{\chi_v}{1+\chi_v}\right]^{-1}\left[\frac{b}{\kappa} - \frac{1}{1+r}\frac{\chi_v}{1+\chi_v}(1-\rho)\left(Z - \frac{f}{\kappa}\right)\right], & \text{if } \frac{f}{\kappa} < Z < \frac{f}{\kappa} + \frac{\frac{b}{\kappa}}{\frac{1}{1+r}\frac{\chi_v}{1+\chi_v}(1-\rho)}, \\ \frac{f}{\kappa} + \frac{b}{\kappa} - \frac{1}{1+r}\frac{\chi_v}{1+\chi_v}(1-\rho)\left(Z - \frac{f}{\kappa}\right), & \text{if } Z \geq \frac{f}{\kappa} + \frac{\frac{b}{\kappa}}{1+r}\frac{\chi_v}{1+\chi_v}(1-\rho). \end{cases}$$

The switch occurs when

$$z_v = \frac{f}{\kappa}$$

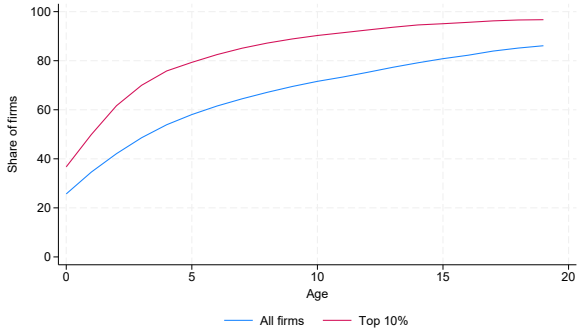
That happens when:

$$Z = \frac{f}{\kappa} + \frac{\frac{b}{\kappa}}{\frac{1}{1+r}\frac{\chi_v}{1+\chi_v}(1-\rho)}$$

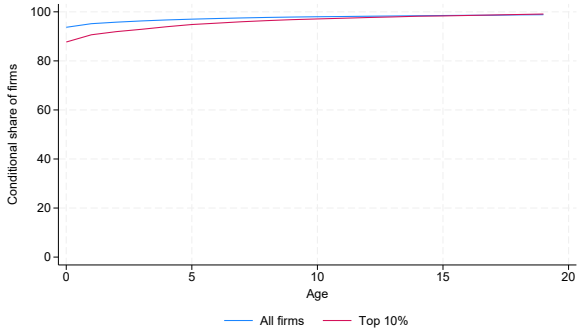
Thus, for firms that will be bad, $\partial z_v/\partial Z = 0$. For more "regular firms" $\partial z_v/\partial Z = -\frac{1}{1+r}\frac{\chi_v}{1+\chi_v}(1-\rho)/\left(1 + \rho\frac{1}{1+r}\frac{\chi_v}{1+\chi_v}\right)$. While for future "superstars" $\partial z_v/\partial Z = -\frac{1}{1+r}\frac{\chi_v}{1+\chi_v}(1-\rho)$. This means that if clearly the firm will be very good, the slope becomes steeper like in the frictionless world. However, note that the slope will still be less steep that in the perfect information case due to $(1-\rho)$.

B Empirical Appendix

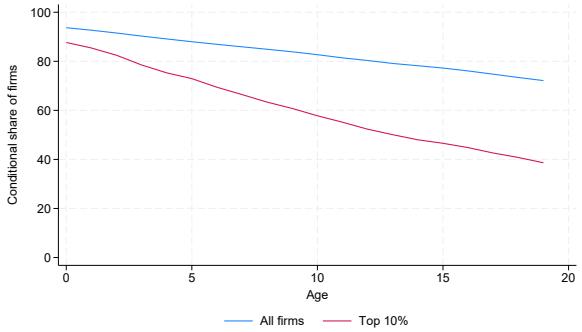
B.1 LTD prevalence



(a) Share of firms that have had any LT debt by age



(b) Share of firms that have had some unsecured LT debt by age (conditional on having had any LT debt)



(c) Share of firms that have had unsecured LT debt only by age (conditional on having had any LT debt)

Figure B1: Prevalence of LT debt by age

These panels illustrate the lifecycle evolution of credit market participation and debt composition using administrative records from the BSD and Companies House (2002–2024). Each plot presents two series: the full sample of incorporated firms (blue line) and the top 10% of firms by employment at each respective age (red line). Panel B1a plots the cumulative share of firms that have accessed any form of long-term debt (LTD) by the indicated age. Panels B1b and B1c restrict the sample to firms with at least one LTD contract. Panel B1b shows the share of borrowers that have utilized CF-LTD at least once, while Panel B1c shows the share that has relied exclusively on CF-LTD throughout their lifecycle.

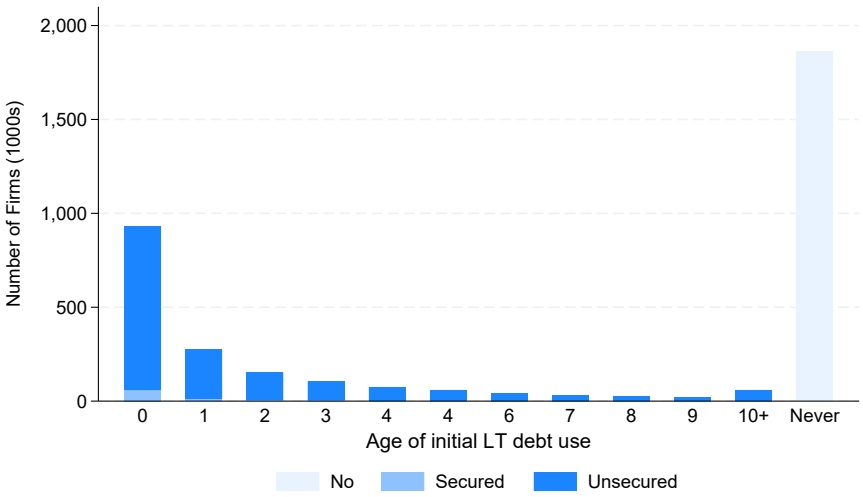
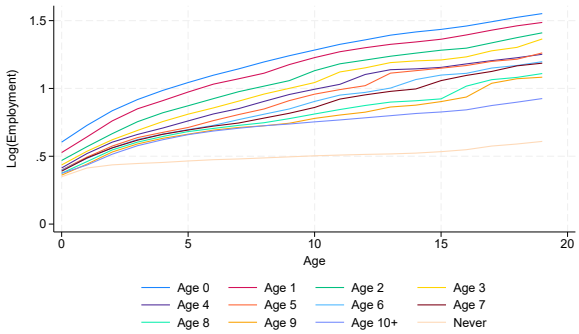


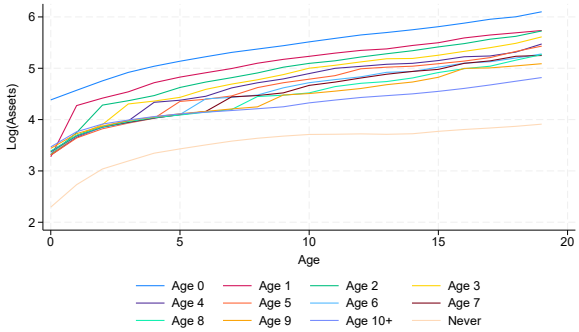
Figure B2: Distribution of age of initial LT debt use

This figure illustrates the lifecycle timing of first-time Long-Term Debt (LTD) issuance for the universe of UK incorporated firms (2002–2024). The vertical axis represents the absolute number of firms entering the credit market at each specific age. For each age cohort, stacked bars decompose these counts into firms whose first lending event was CF-LTD (cash-flow-based) versus A-LTD (asset-backed). The Non-User category denotes the total count of firms that remained unfinanced throughout the sample period. The data is constructed by merging administrative records from the Business Structure Database (BSD) with Companies House records.

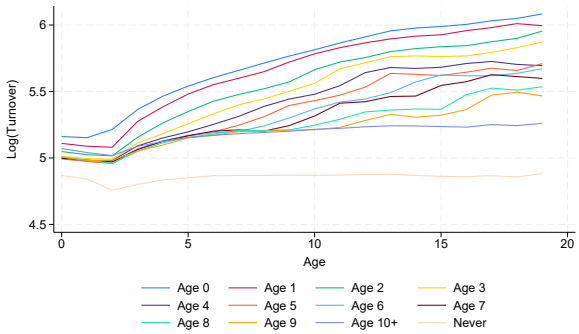
B.2 Finance and firm dynamics



(a) Log(assets) by first use of LT debt



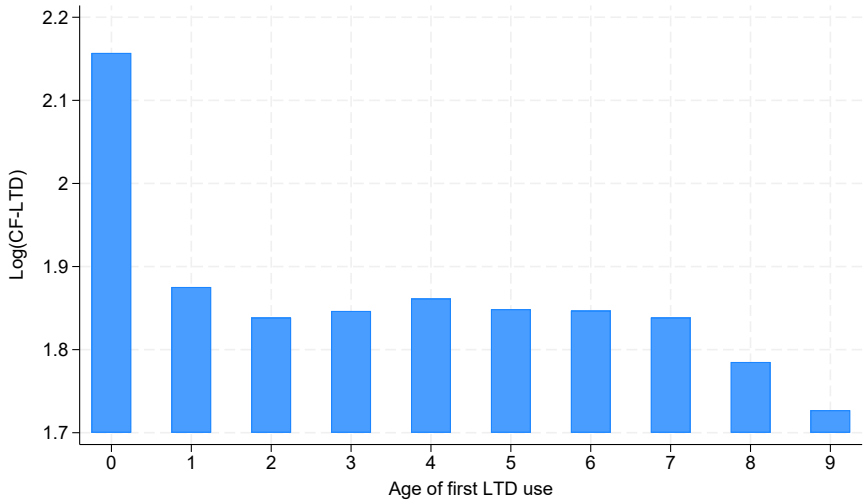
(b) Log(assets) by first use of LT debt



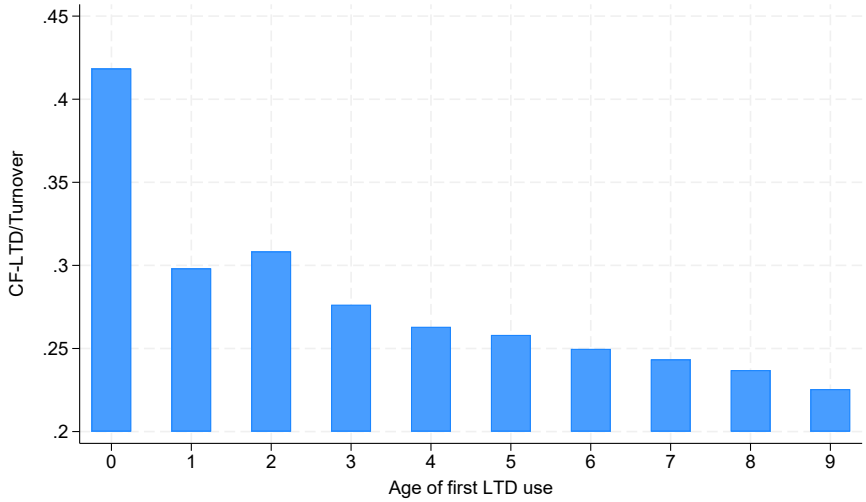
(c) Log(turnover) by first use of LT debt

Figure B3: Firm dynamics by age and first use of LT debt

These panels illustrate the evolution of firm dynamics from age 0 through age 19, stratified by the specific age at which a firm first secured long-term debt. Age 10+ includes firms that receive their initial LTD between ages 10 and 19. Panel B3a has mean log employment as outcome. Panel B3b has mean log assets as outcome. Panel B3c has mean log turnover as outcome. The figures utilize an unbalanced panel of survivors, where the mean at each age is calculated across all firms in the respective cohort that remain active in the Business Structure Database (BSD). This visualization highlights the persistent quality ladder associated with early-stage LTD lending in aggregate, driven by CF-LTD lending.



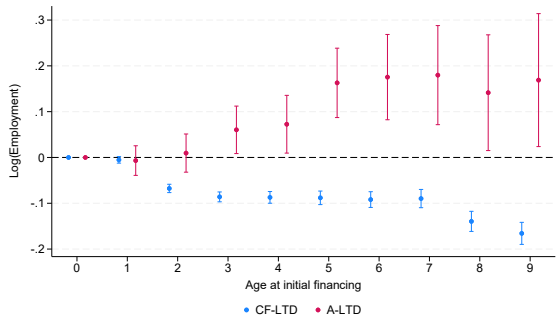
(a) Log(LTD)



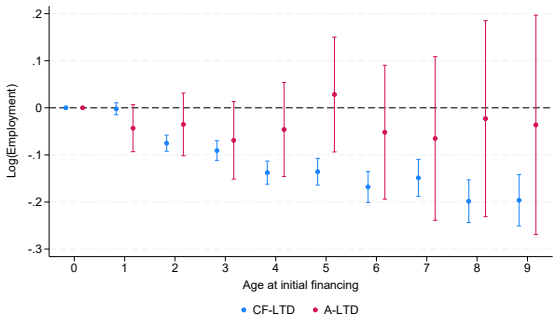
(b) LTD/Turnover

Figure B4: Initial debt scale and intensity for CF-LTD entrants

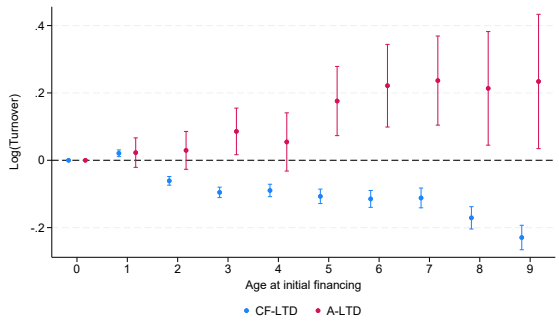
These figures illustrate the scale and intensity of credit at the moment of first-time debt issuance. The sample is restricted to firms whose initial long-term debt (LTD) was a cash-flow-based contract (CF-LTD). Panel B4a plots the natural logarithm of the initial LTD amount, representing the absolute scale of the loan. Panel B4b plots the ratio of initial LTD to annual turnover, representing credit intensity relative to the firm's contemporaneous operations. Results are grouped by the firm's age at the time of its first financing event. All variables are measured in the year of debt origination.



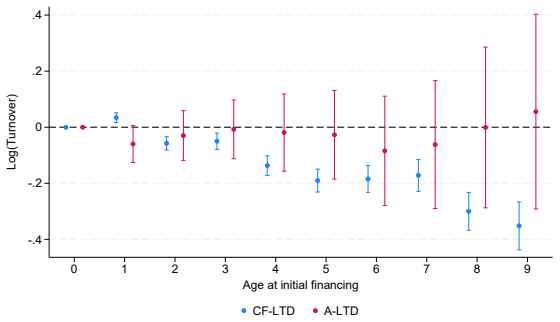
(a) Log(Employment) - 5 years after initial financing



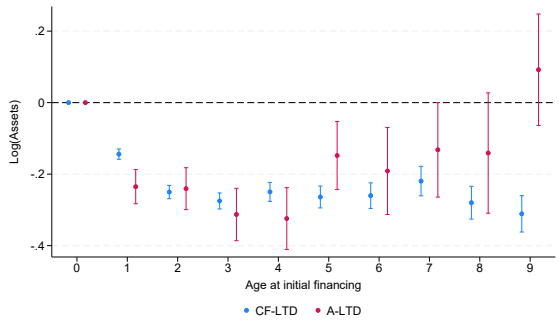
(b) Log(Employment) - 10 years after initial financing



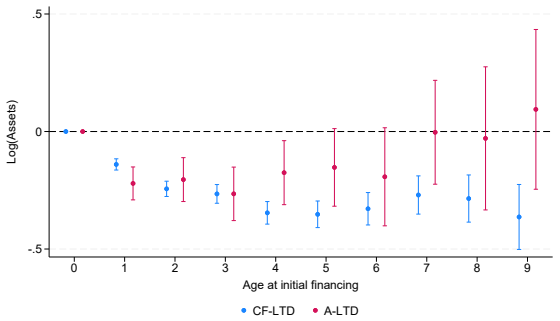
(c) Log(Turnover) - 5 years after initial financing



(d) Log(Turnover) - 10 years after initial financing



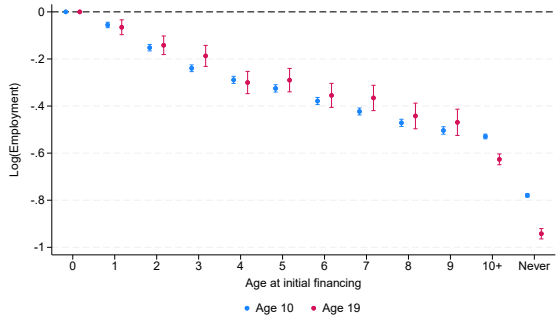
(e) Log(Assets) - 5 years after initial financing



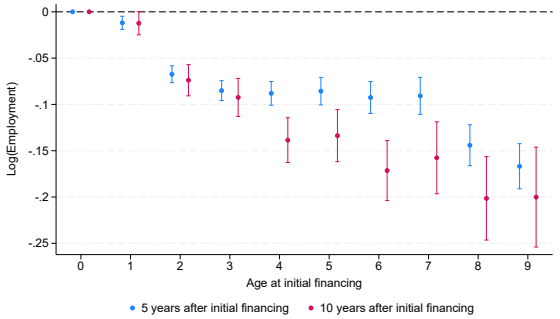
(f) Log(Assets) - 10 years after initial financing

Figure B5: Differences in firm size by age and type of initial LTD financing

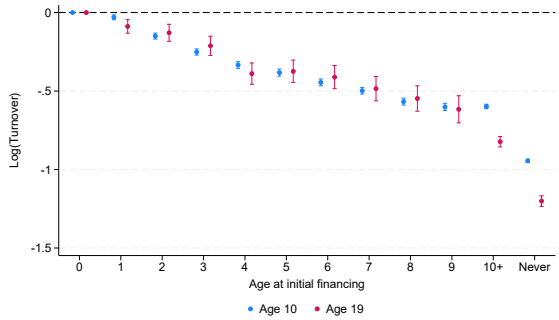
These panels illustrate relative differences in mean log employment, turnover and assets 5 and 10 years after initial financing relative to firms financed with same LTD type at age 0. Estimations are based on equation 2. Panels B5a, B5c and B5e display differences at age 10, while panels B5b, B5d and B5f display differences at age 19. Standard errors use a 90 percent significance level. The figures utilize an unbalanced panel of survivors, where the mean at each age is calculated across all firms in the respective cohort that remain active in the Business Structure Database (BSD). This visualization highlights the persistent quality ladder associated with early-stage cash-flow lending, a pattern that is notably absent in the collateralized debt subsample.



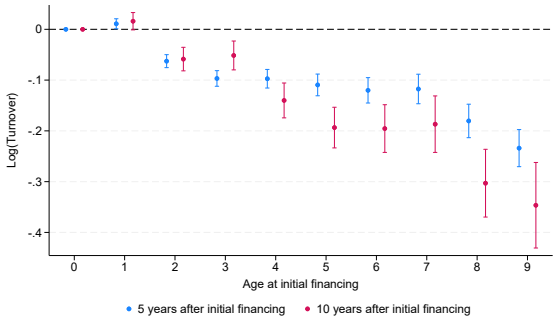
(a) Log(Employment) - Age 10 and 19



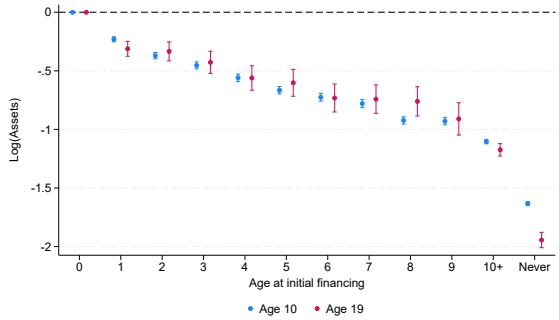
(b) Log(Employment) - 5 and 10 years after initial financing



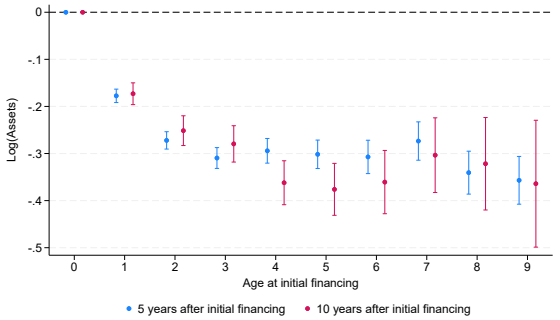
(c) Log(Turnover) - Age 10 and 19



(d) Log(Turnover) - 5 and 10 years after initial financing



(e) Log(Assets) - Age 10 and 19



(f) Log(Assets) - 5 and 10 years after initial financing

Figure B6: Differences in firm size by age and type of initial LTD financing

These panels illustrate relative differences in mean log employment, turnover and assets relative to firms financed with same LTD type at age 0. Estimations are based on equation 2. Panels B6a, B6c and B6e display differences at ages 10 and 19, while panels B6b, B6d and B6f display differences 5 and 10 years after initial financing. Standard errors use a 90 percent significance level. The figures utilize an unbalanced panel of survivors, where the mean at each age is calculated across all firms in the respective cohort that remain active in the Business Structure Database (BSD). This visualization highlights the persistent quality ladder associated with early-stage LTD lending.

B.3 Long Term Debt and the COVID-19 Loan Program

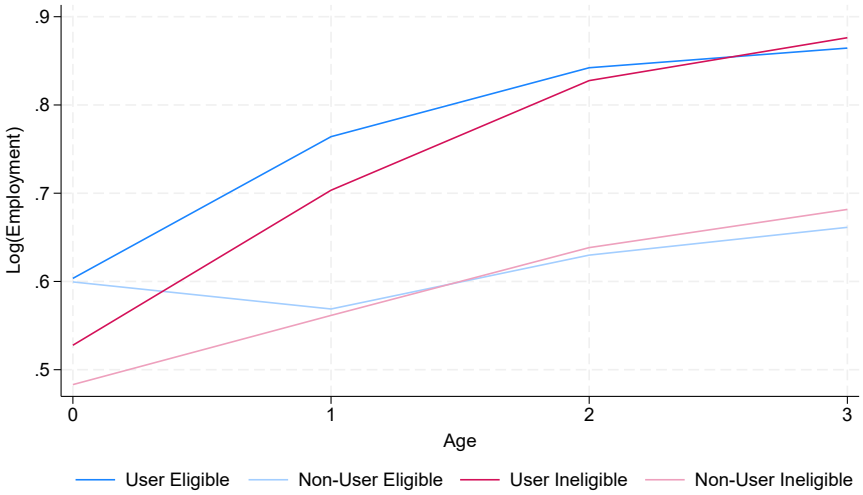
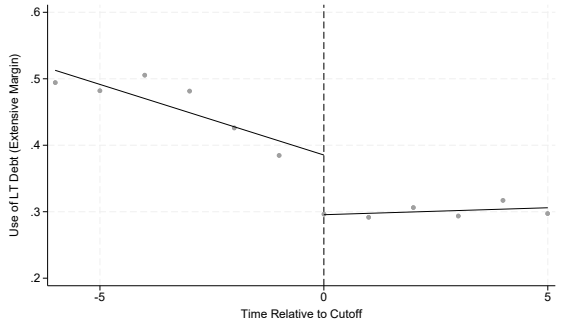
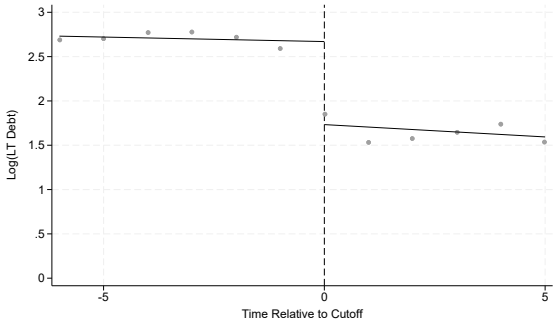


Figure B7: Log(employment) by use of LT debt at start-up and COVID loan eligibility

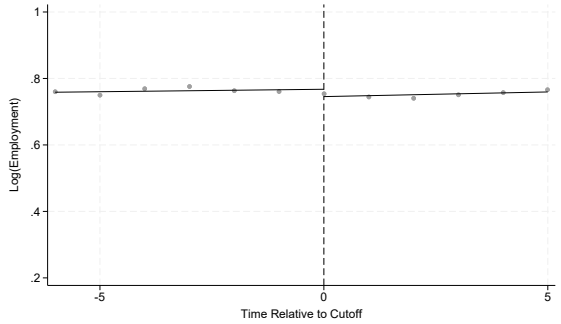
This figure plots mean log employment from Age 0 through Age 3, stratified by BBLS eligibility and CF-LTD take-up at inception. Eligible firms (incorporated in February 2020) had access to 100% government-guaranteed, unscreened BBLS loans, whereas Ineligible firms (incorporated in March 2020) were subject to standard bank screening. Users are defined as firms reporting CF-LTD at Age 0; Non-Users represent the respective unfinanced control groups. The results underscore the informational value of lender screening: while Ineligible Users (screened) initially enter at a smaller scale, they exhibit significantly steeper growth trajectories and outperform Eligible Users by Age 3. A similar pattern of higher unobserved quality is evident among the Non-User Ineligible cohort, who likewise outperform their eligible counterparts. Age 0 corresponds to the firm's initial appearance in the BSD, and all group classifications are fixed at the time of entry.



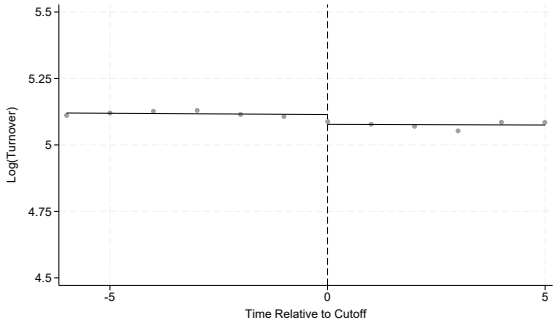
(a) Has LT Debt at age 0



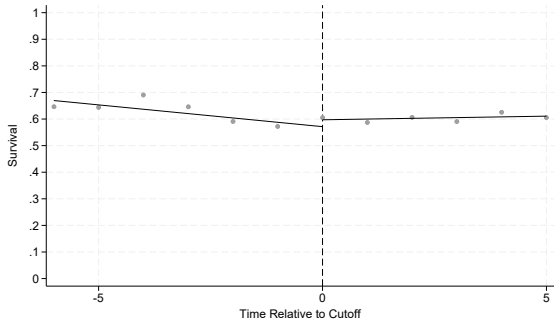
(b) Log(LT Debt) at age 0



(c) Log(Employment) at age 3



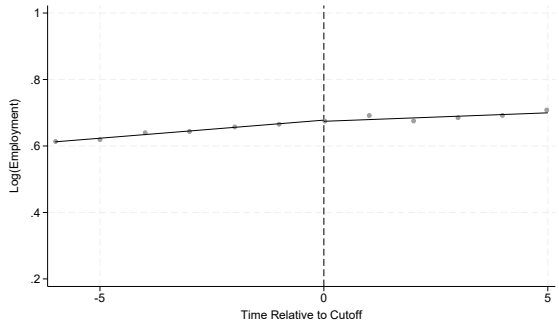
(d) Log(Turnover) at age 3



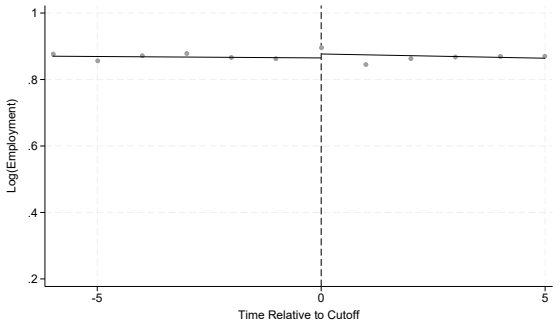
(e) Survival at age 3

Figure B8: RDD plots

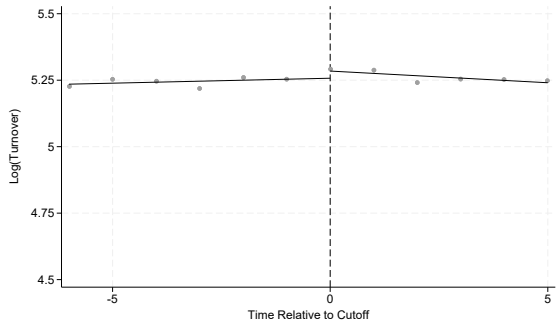
These panels present Regression Discontinuity Design (RDD) estimates using a six-month bandwidth centered on the March 1, 2020, eligibility cutoff. Each data point represents the bin-mean for firms incorporated in a given month. Panel B8a and Panel B8b illustrate the impact on credit access, showing a sharp discontinuity in the probability of securing long-term debt (extensive margin) and the log-transformed debt amount (intensive margin). Panels B8c through B8e plot subsequent real outcomes: log employment at Age 3, log turnover, and survival probability. The figures show that while BBLS eligibility significantly expanded credit access and boosted survival, aggregate real effects on employment and turnover remain statistically indistinguishable across the cutoff. This suggests that when the lender screening channel is suspended—as under the 100% government guarantee—credit allocation becomes decoupled from firm quality, with negative implications for identifying or facilitating the high-growth trajectories seen in screened market-based lending.



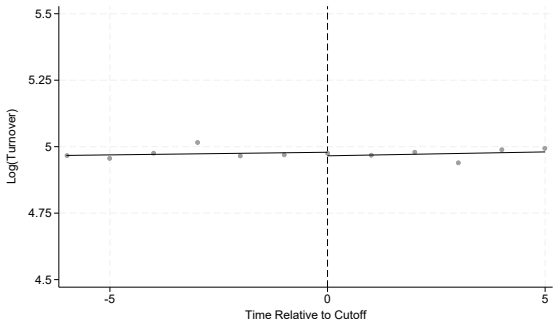
(a) Log(Employment) at age 3 - Non-Users



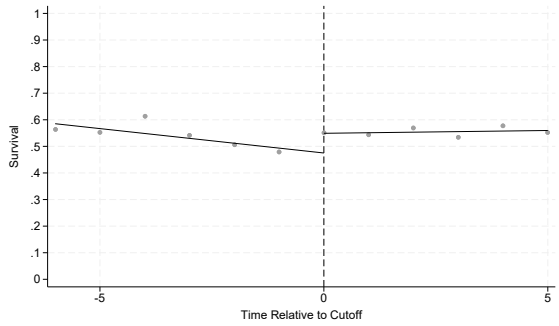
(b) Log(Employment) at age 3 - Users



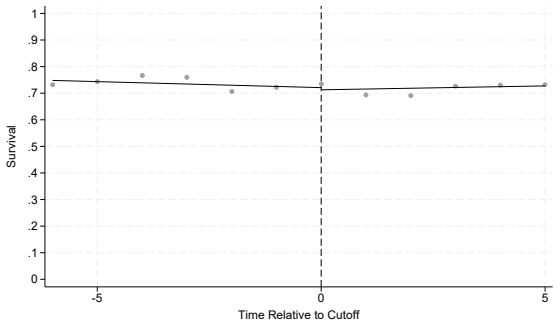
(c) Log(Turnover) at age 3 - Non-Users



(d) Log(Turnover) at age 3 - Users



(e) Survival at age 3 - Non-Users



(f) Survival at age 3 - Users

Figure B9: RDD plots by LT debt use at age 0

These panels present Regression Discontinuity Design (RDD) estimates centered on the March 1, 2020, eligibility cutoff, with the sample partitioned into Users (firms securing CF-LTD at Age 0) and Non-Users. Each data point represents the bin-mean for firms incorporated in a given month within a six-month bandwidth. Panels B9a and B9b illustrate mean log employment for the User and Non-User groups, respectively. Panels B9c and B9d present results for log turnover, while Panels B9e and B9f plot survival probabilities.

Table B1: Summary Statistics: Covid Loan Analysis

		Age 0				**Age 1**		**Age 2**		**Age 3**	
Group	N	Emp.	LT debt	Assets	Turn.	Emp.	Turn.	Emp.	Turn.	Emp.	Turn.
Panel A: Firms born one month before and after BBLS cutoff date											
User Eligible	10,493	0.603	2.812	4.045	4.998	0.764	4.858	0.842	5.057	0.864	5.257
Non-User Eligible	15,465	0.599	–	2.032	4.762	0.569	4.691	0.630	4.804	0.661	4.967
User Ineligible	4,853	0.528	1.877	3.915	4.968	0.703	4.922	0.828	5.063	0.876	5.290
Non-User Ineligible	11,720	0.483	–	2.223	4.836	0.562	4.826	0.638	4.790	0.682	4.972

This table reports mean log-transformed values for employment, long-term debt (LTD), total assets, and turnover across four cohorts defined by BBLS eligibility and credit take-up at inception. Group (1) consists of eligible firms (incorporated in February 2020) that secured LTD at Age 0; Group (2) represents eligible firms without initial LTD; Group (3) consists of ineligible firms (incorporated in March 2020) that secured LTD; and Group (4) represents ineligible firms without initial LTD. At inception (Age 0), statistics are provided for all financial and operational variables. For the subsequent Years 1, 2, and 3, the reported outcomes are restricted to employment and turnover. All group classifications are fixed at the firm's initial entry into the BSD.

Table B2: Regression Discontinuity Design Estimates

	(1) Has LT Debt	(2) Log LT Debt	(3) Log Emp	(4) Log Turn	(5) Log Assets	(6) Survive
Panel 1: Full Sample						
RD Estimate	-0.088^{***}	-0.632^{***}	-0.007	-0.019	-0.063	0.050^{***}
	(0.006)	(0.086)	(0.017)	(0.025)	(0.067)	(0.011)
N	126,071	48,411	77,582	77,582	36,244	126,071
Panel 2: Firms that do not use LT debt at age 0						
RD Estimate	–	–	0.009	0.006	-0.064	0.098^{***}
	–	–	(0.021)	(0.032)	(0.097)	(0.014)
N	–	–	41,854	41,854	20,855	76,992
Panel 3: Firms that use LT debt at age 0						
RD Estimate	–	–	0.033	0.038	0.093	0.013
	–	–	(0.028)	(0.041)	(0.089)	(0.010)
N	–	–	35,728	35,728	15,389	49,079

This table reports local average treatment effects (LATE) at the March 1, 2020, BBLS eligibility cutoff, utilizing a six-month bandwidth based on equation 3. Panel 1 includes the full sample of firms. Panel 2 is restricted to firms that did not secure long-term debt (LTD) at Age 0. Panel 3 is restricted to firms that secured LTD at Age 0. Column (1) is an indicator for initial LTD access; Column (2) is the log-transformed initial LTD amount; Columns (3)–(5) report log employment, log turnover, and log assets, respectively; Column (6) is an indicator for firm survival. The running variable is the firm's month of incorporation. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All non-indicator variables are log-transformed.

B.4 Industry Tangibility and The Predictive Power of CF-LTD

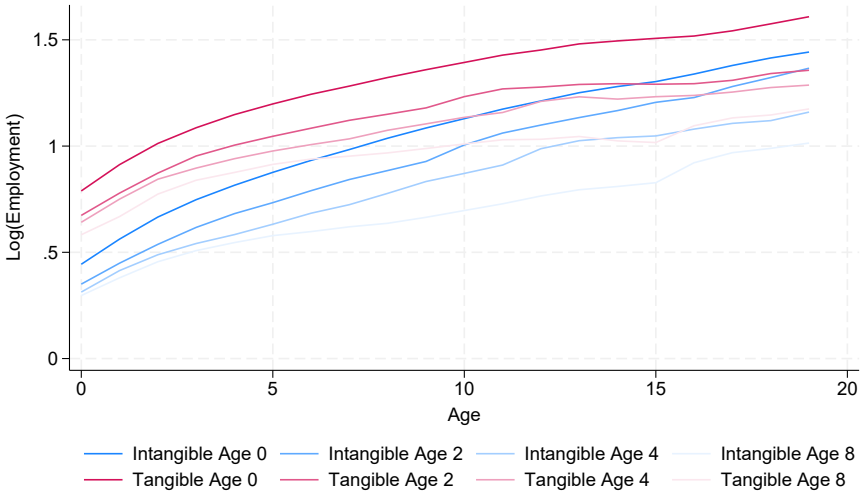


Figure B10: Log(employment) by first use of LT debt and industry tangibility

This figure plots mean log employment trajectories from Age 0 through Age 19, stratified by industry tangibility and the age of initial long-term debt (LTD) financing. Red lines represent high tangible industries, while blue lines denote low tangible industries. Separate trajectories are shown for cohorts receiving their first LTD at ages 0, 2, 4, and 8. The visualization demonstrates that, conditional on securing financing at the same age, intangible firms (blue) typically enter at a smaller initial scale but exhibit significantly steeper growth slopes than tangible firms (red). The figures utilize an unbalanced panel of survivors, where the mean at each age is calculated across all firms in the respective cohort that remain active in the Business Structure Database (BSD).