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Financial Frictions, Borrowing Costs, and Firm Size Across Sectors

Pedro Bento
Texas A&M University

Ashantha Ranasinghe
University of Alberta

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Pedro Bento* Ashantha Ranasinghe†
Texas A&M University University of Alberta

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Abstract

We document new evidence that higher borrowing rates in financially underdeveloped economies are associated with lower investment in productivity, a smaller share of large firms, and smaller average firm size, both in manufacturing and services. To account for these patterns we develop a two-sector economy with heterogeneous entrepreneurs facing financial frictions in the form of high borrowing rates, which rise with the cost of monitoring risky investments. The model is tractable and can be solved analytically, making clear predictions for the impact of high borrowing costs on investment, the share of large firms, and average firm size across sectors, consistent with the evidence we document. Varying monitoring costs to generate observed cross-country differences in borrowing rates, the model can account for one-third of the log-variance of observed average firm size across sectors, over 20 percent of the variation in investment, and a 30 percent drop in aggregate productivity, all substantial relative to the literature.

JEL: O1, O14, O41, O43.

Key Words: financial development, borrowing, firm size, investment, aggregate productivity.

*Department of Economics, Texas A&M University. 254 Liberal Arts Social Sciences Building, College Station, TX, U.S.A., 78743. E-mail: pbento@tamu.edu.

†Department of Economics, University of Alberta. 8-14 Tory Building, Edmonton, AB, Canada, T6G 2H4. E-mail: ranasinghe@ualberta.ca.

1 Introduction

The link between financial development and economic growth has long been thought to be an important part of any explanation for why some countries are drastically poorer and less productive than others. Poorer countries are characterized by low use of formal financial institutions, high borrowing costs, lower investment, small firms on average, and a low share of the labor force employed in large firms. In this paper we study the impact of high borrowing costs driven by financial frictions on firm size and firm-level productivity.

Our contribution is two-fold. First, we document a large range of borrowing costs across countries and show high borrowing costs are associated with lower aggregate productivity, lower investment in productivity, less employment at large firms, and smaller firms (on average) in both manufacturing and services. Second, we develop a tractable quantitative model in which interest rates paid for loans are increasing in the cost of monitoring risky investments. We calibrate the model to match several moments from U.S. aggregate and firm-level data, and find that when monitoring costs are varied enough to generate observed cross-country differences in borrowing rates, model-generated outcomes can account for about one third of the log-variance of observed average firm size in both manufacturing and services, 25 percent of the variance in investment, and 7-12 percent of the observed variance in aggregate total factor productivity (TFP). Relative to our benchmark economy, we find that a 25 percent increase in aggregate gross borrowing rates (aggregate loan payments over aggregate loans) generates a 31-46 percent drop in TFP.

Our focus on borrowing costs is a departure from much of the macroeconomic development literature, which has focused on collateral and other financing constraints, neglecting the high borrowing costs that characterize economies with low financial development. Indeed, workhorse models in the literature suggest that less-financially developed economies should have lower interest rates.[1] We develop a two-sector (manufacturing and services) model

[1] See for instance Buera et al. (2011) who make this point. Financial constraints faced by firms in these models generate a higher shadow cost of funds, which can be interpreted as representing higher borrowing rates. But these implied rates tend to be low relative to those observed in the cross-country data. For

of heterogeneous entrepreneurs who invest in productivity at startup. Entrepreneurs must borrow to finance entry costs and initial investment in productivity, but all other costs over a firm's life can be financed through operating profits. The model is tractable and can be solved analytically, and makes clear predictions for the impact of high borrowing rates on productivity investment, aggregate TFP, and firm-size distributions across sectors, in line with the evidence we document. While we follow Buera et al. (2011) in modeling sectoral differences as arising from differences in non-production costs, the model generates no differential impact across sectors from borrowing costs. We focus on how high monitoring costs raise the cost of borrowing, which reduces risky investment at entry, both in absolute terms and relative to firm revenue, and encourages more firms in equilibrium. We neglect some of the richness captured by workhorse models in the literature (e.g. Buera et al., 2011; Midrigan and Xu, 2014; Moll, 2014), for two reasons. First, to make clear the intuition for how high borrowing rates driven by monitoring costs generate the outcomes we highlight above. Second, to make clear that our framework is complementary to these models in the literature. The mechanism we highlight here can be thought of as operating in addition to other financial frictions like collateral constraints.

We focus on the impact of financial frictions on the decisions of newly formed firms. Recent evidence suggests that decisions made during the early stages of firm formation are significant determinants of firm performance over its life cycle. For example, Haltiwanger et al. (2013) find firms grow substantially more in their first year of life relative to later years. Moreira (2017) shows the investment and scale decisions of entrants depend importantly on the state of the economy at entry, and that these decisions have large and persistent effects over the life of firms. In a cross-country context, Bento and Restuccia (2017) show the impact of misallocation working through investment decisions at entry is much larger than than the impact working through firms' decisions over their life cycle. Focusing on decisions made early in a firm's life cycle is particularly important in the context of financial

example, Midrigan and Xu (2010) generate an average implied rate premium of 5 percent.

frictions. Midrigan and Xu (2014) and Moll (2014), among others, find the aggregate impact of low financial development is dampened by entrepreneur motives to self-finance in order to overcome collateral and other financial constraints, especially when firm-level productivity is persistent. We show that even in an environment where firm-level productivity is constant after entry, high borrowing rates have large effects on firm entry and investment, in addition to aggregate TFP. Our simplifying assumption that new firms must borrow to finance initial investments seems in line with the evidence for poorer countries. Shao (2018) shows that informal financing is not only low in general, but also lower in poorer countries with less financial development.

Greenwood et al. (2020) also consider consider high borrowing rates driven by monitoring costs. They focus on the misallocation of capital across the size distribution of firms, but do not allow for endogenous firm entry nor investment in productivity. Cavalcanti et al. (2021) similarly consider borrowing rates that differ across firms, showing that the resulting misallocation can generate a substantial drop in aggregate TFP. Importantly, Cavalcanti et al. study Brazilian data to determine how borrowing rates depend on firm-level characteristics and the market power of banks. Relevant to our modeling assumptions, they find intermediation costs play a substantial role in generating high borrowing rates, even when accounting for default rates and market power. D'Erasmo and Moscoso-Boedo (2012) focus on informal and formal sector firms in an environment with financial constraints. Their model also generates a negative relationship between financial development and borrowing rates, but predicts more entry and smaller firms in more financially developed economies. In our framework high borrowing rates reduce firm-level investment and increase entry, leading to smaller firms on average. Our work also relates to the more micro-development studies that examine borrowing rates as an impediment to firm growth. A key finding in this literature is that firms in poorer countries face exorbitant borrowing rates. For instance, Banerjee (2003) and Banerjee and Duflo (2005) document that borrowing rates in excess of 50 percent are common in South Asian and African countries, and are often substantially higher. The framework we develop accounts for such high risky borrowing rates and implies that aggregate borrowing rates (across risky and risk-free loans) are negatively related to development.

Our paper contributes to a recent literature exploring the potential determinants of average firm size across sectors and countries. Hsieh and Klenow (2014) and Bento and Restuccia (2017, 2020) show how average size can be lower in economies characterized with a high degree of misallocation and document evidence consistent with this mechanism. Bento (2020) shows that average firm size is lower in economies with high barriers to competition. Workhorse models studying financial frictions can in principle generate a positive relationship between average firm size and financial development, qualitatively consistent with the empirical relationships we document. But calibrated models almost universally predict the opposite relationship. One important exception is Buera et al. (2011), who develop a two-sector model that suggests financial development should lead to smaller firms in manufacturing but larger firms in services. Our model suggests financial development should lead to larger firms in all sectors. We document evidence in support of our model's implications. In particular we show that across countries with data for average firm size in both manufacturing and services, the elasticity of average size with respect to several proxies for financial development (including borrowing rates) is both positive and nearly identical in both sectors. Poschke (2018) goes beyond average firm size, documenting systematic relationships between development and the shape of the firm size distribution. In particular, he provides evidence that the share of employment at large firms is higher in richer countries. We document a similar analogous relationship between financial development (characterized by low borrowing rates) and the employment share of large firms. Our model generates a relationship that is qualitatively consistent with this evidence.

The paper proceeds as follows. In the next section, we document new evidence of the relationships between financial development, borrowing rates, investment in R&D, and firm size distributions across sectors. In Section 3, we present our model and in Section 4.1 we calibrate it to match relevant moments from U.S. data. We use the model to quantify the impact of higher borrowing costs on several outcomes in Sections 4.2 and 4.3. We conclude in Section 5.

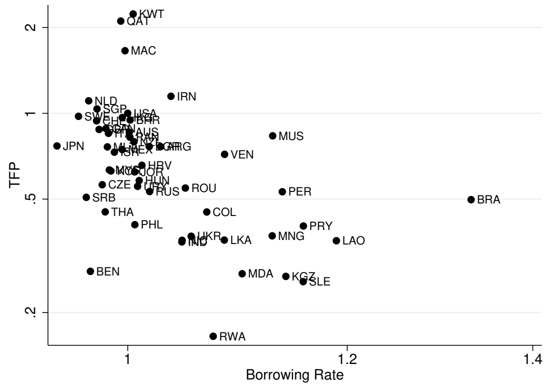
2 Data/Facts

We describe our data and document relationships between average borrowing rates, average firm size in manufacturing and services, R&D intensity, the share of employment in large firms, and aggregate total factor productivity (TFP) across countries. Data on borrowing rates is from the International Monetary Fund's (IMF) International Financial Statistics, and measures the real interest rate paid by private-sector borrowers in 2007. We use measures of gross borrowing rates relative to the U.S.[2] Our establishment size data is from Bento and Restuccia (2017, 2020). It measures the average employment size of establishments in the service sector across 127 economies and in the manufacturing sector across 134 economies. These data are meant to be representative of all persons engaged (employees, owners, etc...) and all establishments (formal and informal) in each sector. Measures of average size in manufacturing reflect an average over available data from each country in the 2000s, while average size in services reflects data from 2007 (or the closest year with data available). We use the share of employment at large firms from Poschke (2018), which measures the share of aggregate private sector employment at firms with at least 250 employees.[3] R&D data is from UNESCO and accounts for all R&D expenditure in an economy, reported relative to GDP. TFP data is from the Penn World Tables v9.0 (Feenstra et al., 2015). We also use two widely-used proxies for financial development. The first is the quantity of bank deposits relative to GDP from Beck et al. (2000, 2009) and Čihák et al. (2012), revised in 2018. Our second proxy is the quantity of external finance to GDP, from Buera et al. (2011). External finance is measured as the sum of private credit, private bond market capitalization, and

[2]For countries without borrowing rate data for 2007, we use data for the closest available year relative to the U.S. in that year.

[3]Poschke's (2018) data comes from the World Bank's World Development Indicators and Amadeus (from Bureau Van Dijk).

Figure 1: Aggregate TFP and Borrowing Rates

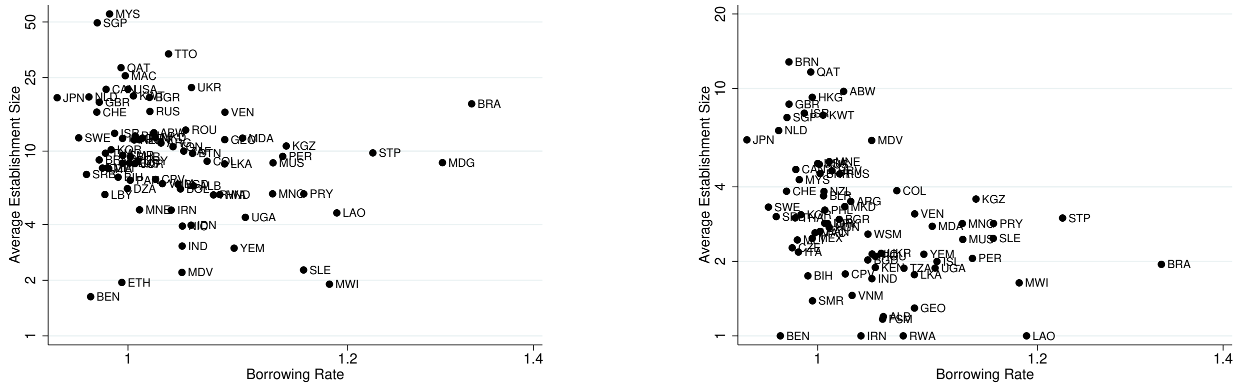


Notes: All variables are shown in log scale. See the text for the definition of variables and sources. The coefficient (standard error) from an OLS regression is -3.95 (1.11).

stock market capitalization. In many models, these ratios are inversely related to the extent of financial frictions.

Figure 1 shows how aggregate TFP is related to borrowing rates across countries. Clearly, economies that feature higher borrowing rates tend to be much less productive. Figure 2 illustrates the relationship between average establishment size and borrowing rates, both in manufacturing and in services. Economies with higher borrowing rates are associated with smaller establishments on average, both in manufacturing and services. For example, the average size of establishments in U.S. manufacturing is 22 and in services is 5. In India, which has a borrowing rate of 13 percent (compared to 8 percent in the U.S.), average sizes in the manufacturing and service sectors are 3.1 and 1.7. Although Figure 2 suggests borrowing rates are associated with larger differences in average size in services, relative to manufacturing, this is largely the result of including different samples of countries. When we regress the ratio of average size in manufacturing to average size in services (for countries with size data for both sectors) on borrowing rates, we find no statistically significant relationship, as illustrated in Figure 3. This suggests a similar relationship between borrowing rates and average establishment size across sectors. We acknowledge that a lack of relationship between financial development and the ratio of average size in manufacturing relative to services is

Figure 2: Establishment Size and Borrowing Rates



(a) Manufacturing

(b) Services

Notes: All variables are shown in log scale. See the text for the definition of variables and sources. The coefficients (standard errors) from OLS regressions are (a) -2.54 (1.40) and (b) -3.81 (0.96).

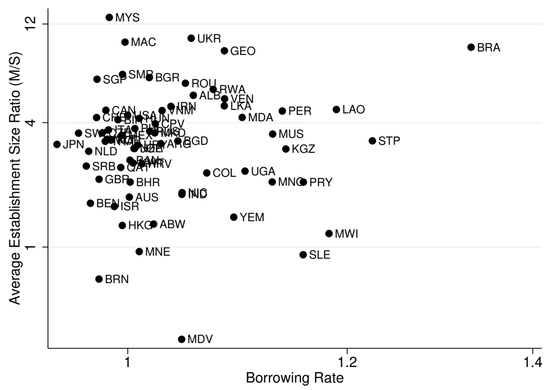
in conflict with the evidence in Buera et al. (2011), who compare average establishment size across sectors in the U.S. and Mexico. They report that sectors with lower average size in the U.S have even lower average size in Mexico, while sectors with high average size in the U.S. have even higher average size in Mexico. In our standardized data (which, importantly, includes establishments with no employees), average size in Mexico is lower than in the U.S., both in manufacturing (9 vs. 22) and in services (2.5 vs. 5). More importantly, this pattern holds across countries with varying levels of financial development.

Figure 4a shows how the share of employment in large firms is related to borrowing rates. The number of countries with both employment share and borrowing rate data is limited, but Figure 4a suggests a clear negative relationship. Economies with low borrowing rates have a larger share of employment in large firms.

Figure 4b illustrates a strong negative relationship between borrowing rates and R&D intensity (aggregate R&D expenditure over GDP). To the extent that R&D intensity can proxy for overall investment in productivity, this points to a potentially important source of observed productivity differences across countries.

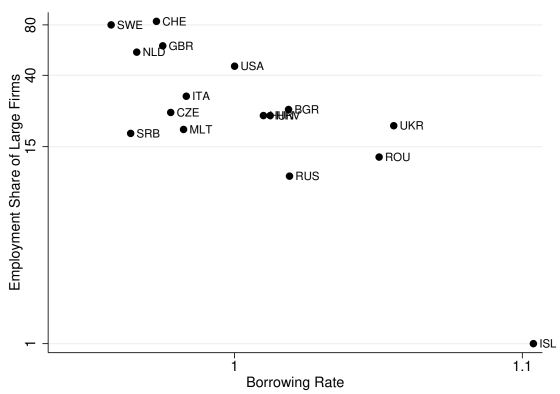
In the model that follows we generate differences in borrowing rates across countries by varying the cost of bank monitoring. While borrowing rates undoubtedly depend also on

Figure 3: Relative Average Size (Manufacturing/Services) and Borrowing Rates

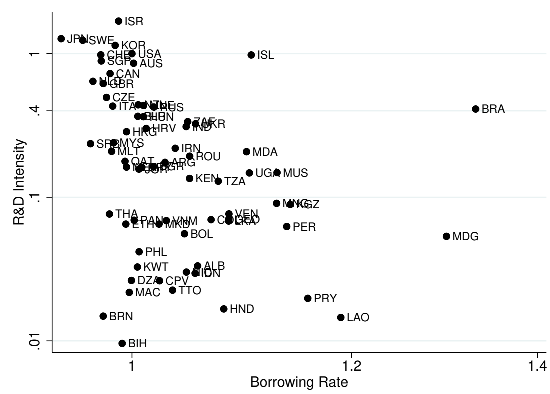


Notes: All variables are shown in log scale. See the text for the definition of variables and sources. The coefficient (standard error) from an OLS regression is 0.41 (1.31), and the lack of significance is robust to excluding outliers.

Figure 4: Employment Share of Large Firms, R&D Intensity, and Borrowing Rates



(a) Employment Share of Large Firms



(b) R&D Intensity

Notes: All variables are shown in log scale. See the text for the definition of variables and sources. The coefficients (standard errors) from OLS regressions are (a) -22.4 (5.9) and (b) -6.33 (2.98).

other factors, the data suggest that banking costs are an important determinant of borrowing rates. For instance, the Global Financial Development Database (GFDD) reports country-level bank overhead/operating costs relative to assets, which is plausibly related to the cost of monitoring. Figure 5 shows a clear positive relationship between bank overhead costs and borrowing rates, and a negative relationship between bank overhead costs and aggregate TFP. The GFDD also reports country-specific measures of bank concentration, which might in part determine borrowing rates. When we control for bank concentration, the estimated elasticity of borrowing rates with respect to overhead does not fall, though concentration does help to explain the variance in borrowing rates across countries.[4] This evidence suggests that overhead costs, of which monitoring costs are presumably an important part, are an important driver of high borrowing rates in poor countries.

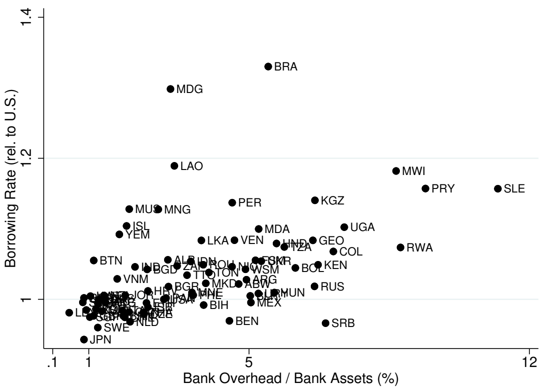
Finally, Figure 6 shows that borrowing rates are highly negatively correlated with two widely-used proxies for financial development. Countries with high borrowing rates have low levels of external finance and bank deposits, relative to GDP. In Appendix A we show each of the relationships illustrated by Figures 2 through 4 are robust to replacing borrowing rates with either of these two proxies for financial development. Across countries, financial development is associated with lower borrowing rates, higher investment in productivity, and larger establishments in both manufacturing and services.

3 Model

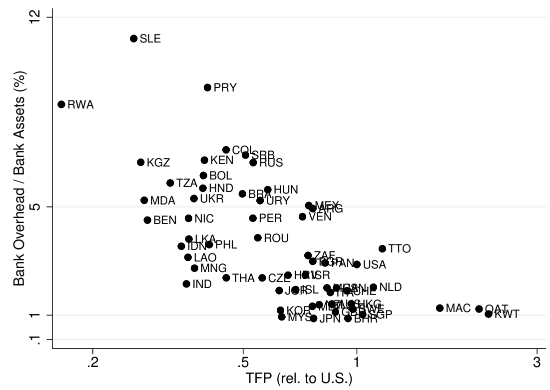
We now present a model that highlights a mechanism through which financial development can affect borrowing rates and generate the patterns just documented. We consider an infinite horizon setting where producers are heterogeneous with respect to productivity and operate in one of two sectors: manufacturing (M) or services (S). After entry, but before producing, firms decide how much to invest in initial productivity. This investment fails with

[4] The OLS-estimated elasticities of borrowing rates with respect to bank overhead and bank concentration are 0.053 (0.007) and 0.041 (0.022), with $R^2 = 0.29$. Without controlling for concentration, the estimated elasticity is 0.046 (0.007), with $R^2 = 0.24$.

Figure 5: Overhead Costs



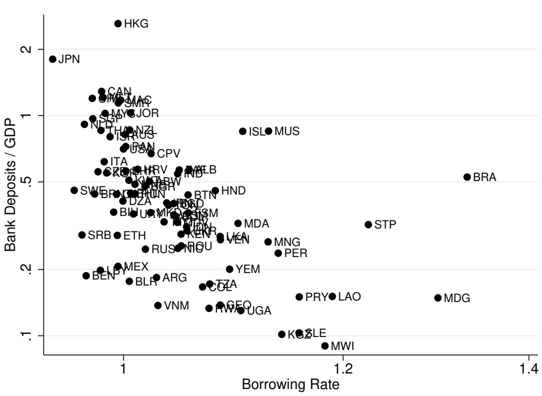
(a) Bank Overhead and Borrowing Rates



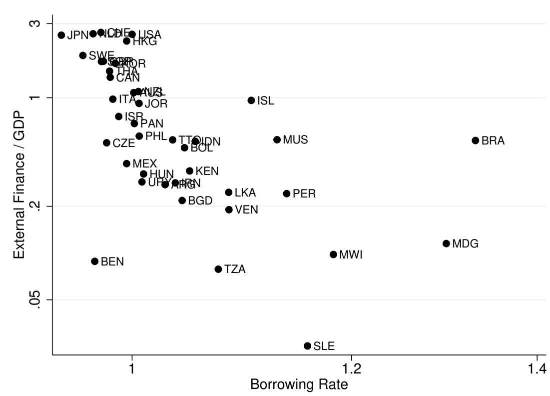
(b) Bank Overhead and TFP

Notes: All variables are in log scale. See the text for the definition of variables and sources. For panel (a), the coefficient (standard error) from an OLS regression is 0.0458 (0.007), with an $R^2 = 0.244$.

Figure 6: Borrowing Rates and Financial Development



(a) Bank Deposits to GDP



(b) External Finance to GDP

Notes: All variables are relative to the U.S. and are shown in log scale. See the text for the definition of variables and sources. The coefficients (standard errors) from OLS regressions are (a) -5.53 (1.50) and (b) -8.32 (2.80).

some probability, and in this case entrants do not produce in the current period but can try investing again in the following period. At entry, firms must borrow to finance both an entry cost and their initial productivity investment. Because failing entrants can invest again, entrants can borrow to finance the entry cost at a risk-free borrowing rate. On the other hand, because we assume firms only pay back investment loans that succeed, they have an incentive to lie about the success of their productivity investments. This implies that banks must incur a cost to monitor firms that claim failure. We characterize financial development by lenders' cost of monitoring these risky investments (Townsend, 1979; Diamond, 1984; Sussman and Zeira, 1995), which we assume is lower in more financially developed economies.

3.1 Environment

We consider a setting with a continuum of consumer-workers of measure L. People can choose to start firms, subject to a sector-specific entry cost, and are heterogeneous with respect to their initial ability to run a firm A_0. We assume ability is drawn from some distribution $F(A_0)$, and that entrants learn their ability only after paying the entry cost and choosing a sector. The choice of sector is permanent and irreversible. Entry costs are specified in terms of the final good and are proportional to the wage: $w \cdot c_{E,i}$, $i \in \{M, S\}$.[5] We assume entrepreneurs continue to earn a wage, consistent with Davis et al. (2009).[6] Before producing, entrants make an initial investment to improve their productivity, after which we assume productivity is fixed over the life-cycle. In Appendix B we show that our results are left essentially unchanged if we allow firms invest in additional productivity improvements over their life-cycle. Given an entrepreneur's ability A_0, the cost of raising productivity to A

[5]Making the entry cost scale up with the wage ensures that the number of firms does not increase with secular growth, consistent with the evidence in Bollard et al. (2010) and Bento and Restuccia (2017, 2020).

[6]Most establishments in the U.S. have no paid employees, and many owners of these establishments maintain employment at other firms. One can interpret our assumption as implying that owners of establishments with less than one unit of optimal labor fulfill all labor requirements themselves, spending the rest of their time working at other firms, while owners of more productive establishments spend all of their time working for their own establishment and pay themselves a wage in addition to any profits.

in sector i is;

$$w \cdot c_{0,i} A_0 (A/A_0)^{\phi}, \quad c_{0,i} > 0, \;\; \phi > 1.$$

The above investment cost is again in terms of the final good and increasing with the wage. Further, it is proportional to an entrant's initial ability, following Atkeson and Burstein (2010).[7] Firms borrow to finance this investment, and are charged a gross borrowing rate $1 + r_b$ that takes into account the lender's cost of monitoring. We assume a bank's cost of monitoring an investment is;

$$b \cdot m \cdot \left(\frac{A/A_0}{\overline{A/A_0}} \right)^{\gamma}, \;\; m \geq 0, \;\; \gamma \geq 0,$$

where b is the amount borrowed, m is an inverse measure of monitoring technology and $\overline{A/A_0}$ is an average across firms. $\gamma > 0$ implies that monitoring costs are increasing in the productivity increase chosen by the entrant, relative to that chosen by other firms. This last assumption follows Anzoategui (2014), and is consistent with the evidence in Gorman and Sahlman (1989), Blackwell and Winters (1997), Hellmann and Puri (2002), and Hall and Lerner (2010).[8] Given an exogenous probability of success q and given our assumption that entrepreneurs pay back this loan only when successful, the profit of a bank from lending b is;

$$q \cdot (1 + r_b) \cdot b - b - (1 - q) \cdot b \cdot m \cdot \left(\frac{A/A_0}{\overline{A/A_0}} \right)^{\gamma},$$

where bank monitoring is contingent on the firm claiming failure. Assuming zero bank profits, this implies a gross borrowing rate equal to;

$$1 + r_b = \frac{1 + m \cdot \left(\frac{A/A_0}{\overline{A/A_0}} \right)^{\gamma} (1 - q)}{q}. \tag{1}$$

[7]This ensures both the marginal benefit and marginal cost of productivity investment is increasing in an entrepreneur's ability. This serves to remove any heterogeneity in investment across firms.

[8]This literature documents evidence that both investment by new firms and loans used to finance innovation are charged higher borrowing rates.

There is an exogenous probability of producer exit represented by $0 < \lambda < 1$, which is common across sectors.[9] We denote the total number of firms in sector i by M_i (which includes entrants with unsuccessful investments), and the total number of workers by L_i. Average firm size in sector i is therefore;

$$size_i = \frac{L_i}{M_i}. \tag{2}$$

Finally, we denote the number of producing firms by N_i.

3.2 Sector and firm-level production

Aggregate output in the economy is produced by a representative final-good firm that combines output produced in the manufacturing and service sector;

$$Y = Y_M^{\eta} Y_S^{1-\eta}.$$

Profit maximization for the final-good firm implies;

$$P_M Y_M = \eta Y, \quad P_S Y_S = (1-\eta) Y,$$

and we assume the aggregate good serves as the numéraire.

Output in manufacturing and services are an aggregation of firm-level production in their respective sectors. Firm-level production is $y = (Az_i)^{1-\alpha} \ell^{\alpha}$, $0 < \alpha < 1$, where z_i is sector-specific productivity common to all firms in sector i, and ℓ is labour.[10] A producer with productivity A chooses labor to maximize operating profits in each period, resulting in the

[9] We assume that entrepreneurs who choose to start a new firm after exiting must again draw from the ability distribution.

[10] As our focus is on frictions affecting productivity investment at entry, we abstract from capital in production. Including frictions that limit access to capital would serve to amplify the impact of aggregate TFP differences on aggregate output in the usual way.

following optimal labor, output, and operating profits;

$$\ell(A) = Az_i P_i^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{w}\right)^{\frac{1}{1-\alpha}}. \tag{3}$$

$$y(A) = Az_i P_i^{\frac{\alpha}{1-\alpha}} \left(\frac{\alpha}{w}\right)^{\frac{\alpha}{1-\alpha}}. \tag{4}$$

$$\pi_i(A) = Az_i P_i^{\frac{1}{1-\alpha}} (1-\alpha) \left(\frac{\alpha}{w}\right)^{\frac{\alpha}{1-\alpha}}. \tag{5}$$

3.3 Productivity Investment

Entrants choose initial productivity A to maximize $V_i(A \mid A_0)$, defined as follows;

$$V_i(A \mid A_0) = -q \cdot wc_{0,i} A_0 (A/A_0)^{\phi} (1 + r_b) + \frac{q\pi_i(A)}{1-\rho} + \left(\frac{1-q}{1+r}\right) V_i(A' \mid A_0),$$

where q is the probability with which the loan is repaid, $(1+r_b)$ is as in equation (1), $\rho \equiv \frac{1-\lambda}{1+r}$, and A' refers to a potential future choice of A if current investment fails. The solution to this problem is;

$$wc_{0,i} A_0 (A/A_0)_i^{\phi} = \left(\frac{q}{1-\rho}\right) \frac{\pi_i(A)}{\phi + (\phi+\gamma)m(1-q)}, \tag{6}$$

which already takes into account that an entrepreneur's choice of (A/A_0) is independent of A_0 and so is constant across firms within a sector. We can now express the value of an entrant, given A_0, as;

$$V_i(A_0) = \pi_i(A_0 \cdot (A/A_0)_i) \left(\frac{q}{1-\rho}\right) \left(\frac{1+r}{r+q}\right) \left(\frac{\phi - 1 + (\phi - 1 + \gamma)m(1-q)}{\phi + (\phi+\gamma)m(1-q)}\right), \tag{7}$$

with $(A/A_0)_i$ given by equation (6).

3.4 Equilibrium conditions

We now derive the equilibrium conditions of the model. Using equation (3), labor market clearing in sector i implies;

$$L_i = N_i \mathbb{E}(A_i) z_i P_i^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{w}\right)^{\frac{1}{1-\alpha}},$$

where N_i denotes the number of producers in i and $\mathbb{E}(A_i)$ refers to the average A across producers in sector i, equal to;

$$\mathbb{E}(A_i) = \mathbb{E}(A_0)(A/A_0)_i.$$

Combining the above expressions with equation (5), operating profits for a producer with initial productivity draw A_0 can now be expressed as;

$$\pi_i(A_0 \cdot (A/A_0)_i) = w\left(\frac{1-\alpha}{\alpha}\right)\frac{A_0 \cdot (L_i/N_i)}{\mathbb{E}(A_0)}. \tag{8}$$

Free entry ensures that the cost of entering is equal to the expected value of an entrant, and that the value of entering (net of entry costs) is the same across sectors;

$$wc_{E,i} = \mathbb{E}[V_i(A_0)]. \tag{9}$$

Combining the above condition with equations (7) and (8) results in the following expression for the average size of producers (not all firms) in sector i;

$$\frac{L_i}{N_i} = \frac{\alpha c_{E,i}(1-\rho)}{q(1-\alpha)}\left(\frac{r+q}{1+r}\right)\left(\frac{\phi+(\phi+\gamma)m(1-q)}{\phi-1+(\phi-1+\gamma)m(1-q)}\right). \tag{10}$$

We assume a steady state equilibrium with a constant number of firms M_i. Let E_i denote the number of entrants in sector i. Then the number of producers N_i is equal to the number of surviving producers from the previous period, plus the number of new entrants with successful initial investments, plus the number of failed previous entrants that succeed in the current period. Since N and E are constant over time in steady state, this implies the following relationship;

$$N_i = (1-\lambda)N_i + q(E_i + E_i(1-q) + E_i(1-q)^2 + E_i(1-q)^3 + ...) = \frac{E_i}{\lambda}.$$

The total number of firms in sector i (producers and failed investors) is therefore;

$$M_i = N_i + E_i(1-q)(1 + (1-q) + (1-q)^2 + ...) = N_i \left(\frac{\lambda + (1-\lambda)q}{q} \right). \tag{11}$$

Combining the above expression with equation (10), we obtain the following expression for average firm size (across all firms) in sector i;

$$size_i = \frac{\alpha c_{E,i}(1-\rho)}{(\lambda + (1-\lambda)q)(1-\alpha)} \left(\frac{r+q}{1+r} \right) \cdot \left(\frac{\phi + (\phi+\gamma)m(1-q)}{\phi - 1 + (\phi - 1 + \gamma)m(1-q)} \right). \tag{12}$$

Using equations (6) and (9) we can express optimal initial productivity as;

$$(A/A_0)_i^{\phi} = \frac{c_{E,i}(r+q)}{c_{0,i}(1+r)\mathbb{E}(A_0)\left[\phi - 1 + (\phi + \gamma - 1)m(1-q)\right]}. \tag{13}$$

Average firm size in each sector is increasing in financial development, as a lower m raises the last term in (12). Equation (13) makes clear that (A/A_0) is increasing in financial development (lower m). The intuition is straightforward – as the cost of improving productivity decreases, entrants choose a higher initial productivity. Further, a lower m encourages entrants to invest a higher *share* of future profits in productivity. As a result, for a given number of firms, the value of entry is lower. This leads to less entry, fewer firms, and a larger average firm size. Together, equations (12) and (13) also imply that the impact of a higher monitoring cost m on both average size and firm-level productivity will be proportionately the same in both sectors. As a result, a higher m lowers average size and firm-level productivity in both manufacturing and services, but does not affect the relative size nor relative productivity across sectors. We also note that sector specific productivity z_i has no impact on optimal investment in productivity or average firm size. In anticipation of our quantitative exercise in Section 4, we note here that the proportional changes in average size and (A/A_0) due to changes in m are independent of α, λ, r, $\mathbb{E}(A_0)$, $c_{E,i}$, and $c_{0,i}$.

To see how the share of employment in large firms is affected by higher monitoring costs, note that labor market clearing combined with equations (3) and (11) imply firm-level employment in equilibrium as a function of an entrepreneur's initial ability is equal to;

$$\ell_i(A_0) = \frac{A_0}{\mathbb{E}(A_0)} \cdot \frac{L_i}{N_i} = \frac{A_0}{\mathbb{E}(A_0)} \cdot size_i \left(\frac{\lambda + (1-\lambda)q}{q} \right). \tag{14}$$

In Section 2 we showed that high borrowing costs are associated with a lower share of employment in firms with at least 250 employees. Here we can use the above expression to derive the threshold ability A_0^{250} at which a firm hires 250 employees;

$$A_{0,i}^{250} = \frac{250}{size_i} \mathbb{E}(A_0) \left(\frac{q}{\lambda + (1-\lambda)q} \right). \tag{15}$$

From the above equation, a decrease in average firm size within a sector due to higher borrowing rates raises the ability at which a firm chooses to hire 250 employees. This implies a lower fraction of firms will be described as 'large.' At the same time equation (14) shows that lower average firm size reduces optimal employment for any given ability. Taken together, equations (14) and (15) show the share of employment in large firms must decrease as borrowing costs increase.

Given all of the above, output per person in a sector is equal to

$$\frac{Y_i}{L_i} = TFP_i = \left(\frac{z_i \mathbb{E}(A_i)}{size_i} \right)^{1-\alpha} \left(\frac{q}{\lambda + (1-\lambda)q} \right)^{1-\alpha} = \frac{w}{\alpha P_i},$$

and aggregate output is

$$\frac{Y}{L} = TFP = \eta^\eta (1-\eta)^{1-\eta} \left(\frac{\mathbb{E}(A_M)^\eta \mathbb{E}(A_S)^{1-\eta}}{size_M^\eta size_S^{1-\eta}} z_M^\eta z_S^{1-\eta} \right)^{1-\alpha} \left(\frac{q}{\lambda + (1-\lambda)q} \right)^{1-\alpha}. \tag{16}$$

The equilibrium wage and employment shares are

$$w = \alpha \cdot \frac{Y}{L}, \quad \frac{L_M}{L} = \eta, \quad \text{and} \quad \frac{L_S}{L} = 1 - \eta.$$

It also follows that relative sectoral prices are inversely related to relative TFP, as is standard.

Two other outcomes are of interest here. First, the ratio of aggregate investment in productivity relative to aggregate output is;

$$Inv.\ Ratio = \frac{\lambda(1-\alpha)}{(1-\rho)[\phi + (\phi+\gamma)m(1-q)]}. \tag{17}$$

Second, the aggregate gross borrowing rate (across loans to finance entry and initial productivity investment) is equal to total payments owed relative to total loans;

$$\overline{1 + r_b} = \frac{q(1+r)[\phi - 1 + (\phi+\gamma-1)m(1-q)] + (r+q)[1 + m(1-q)]}{q(1+r)[\phi - 1 + (\phi+\gamma-1)m(1-q)] + r + q}. \tag{18}$$

We note that for a given γ, an increase in monitoring costs m will decrease investment and increase the borrowing rate. When $\gamma = 0$ an increase in m has a bigger impact on the borrowing rate than investment. In contrast, for high values of γ an increase in m has a smaller impact on the borrowing rate than investment. This suggests there exists a value for γ such that variation in m generates a relationship between investment and the borrowing rate that is roughly consistent with the data. We exploit this in our calibration in the next section.

4 Quantitative Analysis

We now evaluate the quantitative relevance of our framework. We begin by discussing the calibration of the model and how key parameters are identified from the data. We then quantify the impact of financial frictions on investment, firm size, and productivity across sectors. We also evaluate how well our model predictions across sectors and spanning a spectrum of financial market development fits with the facts in the data.

4.1 Calibration

To evaluate the quantitative importance of our framework for firm investment and size, we calibrate the parameters in the model to match relevant statistics in the U.S. economy. In this regard, we follow the literature on financial frictions and treat the U.S. as a natural benchmark given its well-developed financial markets.

There are 8 parameters and a distribution to calibrate: the labor elasticity of firm output α; the probability of exit λ; the probability of a successful initial investment q; the risk-free rate r; the convexity parameter in the investment cost function ϕ; the fixed cost of monitoring in our benchmark U.S. economy m_{US}; the elasticity of monitoring costs with respect to initial productivity γ; cost of entry $c_{E,i}$; and a distribution of ability across the population. As our goal here is to quantify the factor change in outcomes due to an increase in monitoring costs, we can ignore parameter values for η, z_i and $c_{0,i}$ since they do not interact with monitoring cost m. We follow the literature in setting $\alpha = 0.8$, $\lambda = 0.1$, and $r = 0.04$. The ability distribution and the remaining parameters are chosen to match relevant moments in the U.S. economy as we describe next.

In our framework, ϕ is the elasticity of investment in productivity at entry with respect to output. We set $\phi = 1.39$ targeting the same moment in Bento and Restuccia (2017), who model entry investment in a similar way. The cost of entry $c_{E,i}$ is chosen to target average size in each sector, which is 22 and 5 workers in manufacturing and services (Bento and Restuccia, 2020).[11]

In the model, q is the probability of success for initial productivity investment. We set this equal to 0.64 to be consistent with Fairlie et al. (2018), who report a two-year survival rate of new firms in the U.S. equal to 0.41. Our identifying assumption here is that entrants

[11] Although we refer to 'firms' throughout for ease of exposition, our calibration of $c_{E,i}$ targets the average size of establishments from Bento and Restuccia (2020). We emphasize this inconsistency is not important for our results, as the levels of $c_{E,i}$ do not affect the proportional impact on average size from changes in monitoring costs m.

who do not succeed in their initial investment are counted as exiting firms in the data, but immediately start a 'new' business by investing again (without re-incurring the entry cost).

To calculate how the share of employment in large firms changes with monitoring costs, we require a distribution for ability. Equation (14) shows that relative firm-level employment is proportional to ability. We therefore choose a distribution in the following way. First, we note that the employment share of manufacturing firms with at least 500 employees in the U.S. is 11 percent lower than the employment share of firms with at least 250 employees. To interpret this we assume employment across firms is described by a Pareto distribution with scale parameter κ. Since the ability A_0 corresponding to 500 employees is double that corresponding to 250 employees, and noting that all firms have the same proportional productivity increase, we choose a value for κ such that the employment share of firms with at least 500 employees relative to the that of firms with at least 250 employees is equal to 0.89:

$$\left(\frac{A_0^{500}}{A_0^{250}}\right)^{1-\kappa} = 2^{1-\kappa} = 0.89.$$

We obtain $\kappa = 1.17$. We emphasize that we do not need this parameterized distribution to accurately describe the entire firm size distribution, only the range of the distribution around A_0^{250} in the U.S.

From equation (18) the aggregate gross borrowing rate can be expressed as a function of parameters we now have values for, as well as m and γ. Since there are no direct estimates we can rely on to gauge institutional differences in monitoring costs, we proceed as follows. Our choice of γ affects the differential impact of m on aggregate borrowing rates and the aggregate investment ratio, hence we choose γ and m_{US} in the following way. For a given γ, we use (18) to infer m_{US} by targeting an aggregate gross borrowing rate $(\overline{1 + r_b})$ of 1.039 for the U.S. from the IMF data (calculated relative to the gross risk-free rate). We can then target higher aggregate borrowing rates by choosing monitoring costs m accordingly. We choose γ such that when we estimate the elasticity of the model-generated investment ratio with respect to borrowing rates in our simulated data, we obtain the same value as the estimated elasticity of observed R&D intensity with respect to borrowing rates reported in Figure 4b (-6.33). We obtain $\gamma = 2.8$ and $m_{US} = 0.17$, and find an aggregate borrowing rate 20 percent higher than in the U.S. can be generated by $m = m_{US} \cdot 24$.

4.2 Results

We now evaluate the quantitative importance of differences in borrowing rates stemming from high monitoring costs in less developed financial markets. To this end, we adjust the monitoring cost parameter m to reflect aggregate borrowing rates across countries spanning a spectrum of financial development, holding all other parameters fixed, and evaluate its impact on investment, firm size, and TFP. We emphasize that we do not think countries with varying levels of financial development differ only due to differences in monitoring costs. Rather, this exercise serves to isolate the impact of monitoring costs on outcomes of interest and thus allows us to evaluate the quantitative relevance of our primary mechanism in the cross-country data. Note that our approach here is similar in spirit to that taken in much of the quantitative literature.[12]

Table 1 shows how the borrowing rate for risky investments, average firm size across sectors, the employment share of large firms, investment, and aggregate TFP change as we increase monitoring costs enough to generate a 25 percent higher aggregate gross borrowing rate relative to the U.S. (first row). This range captures most of the cross-country variation in borrowing rates observed in Section 2. All outcomes are calculated using equations (1), (12), (15), (16), (17), and (18). The aggregate gross borrowing rate, investment ratio, and TFP are reported relative to the U.S. values.[13] Note that because variation in m has proportionate effects across sectors, columns 2 and 7 should be understood to represent both sectors, as well as the aggregate.

[12] For instance, workhorse models of financial frictions adjust a parameter that affects collateral requirements that are tied to financial market development (e.g. Buera et al., 2011; Midrigan and Xu, 2014; Moll, 2014).

[13] The employment share of large firms is also calculated relative to the U.S., then multiplied by the observed share in the U.S. from Figure 4a.

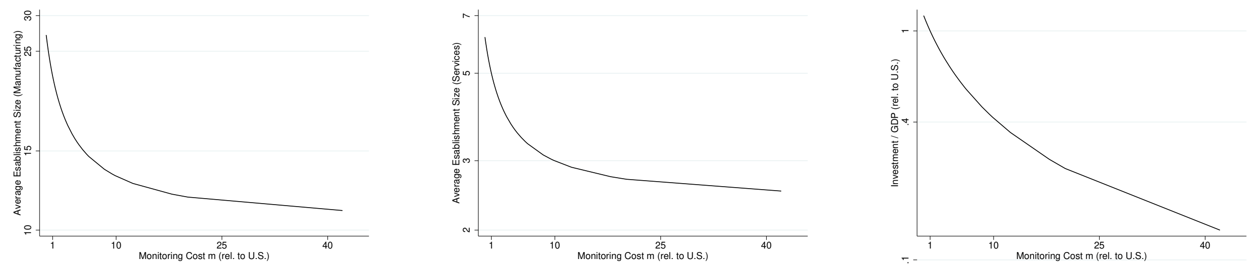
Table 1: Model Results Across Values of m: $\alpha = 0.8$

Aggregate $\overline{1+r_b}$	Risky $1{+}r_b$	Average Size (M)	Average Size (S)	Emp. Share Large Firms (%)	Investment Ratio	TFP
1.00	1.66	22	5.0	45	1.00	1.00
1.05	1.84	17	4.0	44	0.77	0.98
1.10	2.12	15	3.4	42	0.57	0.94
1.15	2.64	13	2.9	41	0.39	0.90
1.20	3.89	12	2.6	41	0.22	0.83
1.25	11.3	11	2.4	40	0.06	0.69

The are several points highlighted in the table. First, the gross risky borrowing rate in the economy with the highest monitoring cost is about 6.8 times higher than in the U.S. This is consistent with the very high borrowing rates many small businesses in countries with under-developed financial markets face as documented in Banerjee (2003) and Banerjee and Duflo (2005). For comparison, a risky rate of 1030 percent is equivalent to a monthly rate of 22 percent, a rate commonly charged by pawn shops across North America. Second, financial market development (moving up in the table) is negatively related to borrowing rates and positively related to average firm size in manufacturing and services. For instance, raising m enough to generate a 25 percent higher aggregate borrowing rate relative to the U.S. results in average firm size in manufacturing falling to 11 employees (from 22) and in services to 2.4 employees (from 5). In this regard, while much of the quantitative work on financial frictions abstract from average firm size or predicts that higher financial market development should reduce average size, our model captures the relationship in the data that average firm size rises with financial market development in all sectors. The model predicts a small drop in the employment share of large firms, equal to 12 percent when the aggregate borrowing rate increases by 25 percent. Finally, we find financial market development has no effect on the relative size of manufacturing firms, relative to service-sector firms, which is also consistent with the data.

Worsening financial market development (moving down on the table) also lowers the

Figure 7: Monitoring Costs, Average Size and Investment



(a) Average Size (Man.) (b) Average Size (Serv.) (c) Investment

Notes: Figures show the impact on a) average size in manufacturing, b) average size in services, and c) investment in productivity relative to aggregate output when monitoring costs are increased up to 40 times the U.S. value.

share of output going to investment, lowering both firm-level and aggregate productivity (TFP). The impact on TFP is partially offset by the drop in average firm size, since the production technology features decreasing returns to labor. Nevertheless, an economy that has a 25 percent higher aggregate borrowing rate has a 94 percent lower investment ratio, and 31 percent lower TFP. Our framework can therefore rationalize the large differences in investment across countries, as well as a significant portion of the large differences in TFP. Further, the impact of monitoring costs on TFP is large relative to what is found in the existing literature on financial frictions.

Table 1 shows outcomes associated with different aggregate borrowing rates, where different borrowing rates are generated by varying the cost of monitoring m. Figure 7 illustrates directly how outcomes are related to the monitoring cost. Of note, much of the decreases in size and investment are achieved for monitoring costs in the range of 10 times the U.S. level.

In the above exercise we assume $\alpha = 0.8$, which implies that changes in firm-level productivity translate to relatively small changes in TFP. If we instead assume $\alpha = 2/3$, as in Hsieh and Klenow (2009, 2014) for example, the recalibrated model generates the same outcomes with respect to borrowing rates, firm size, and investment, but a much larger impact on TFP. For example when the aggregate gross borrowing rate increases to 25 percent above the benchmark U.S. level, TFP drops by 46 percent (compared to 31 percent in Table 1).

4.2.1 Sectoral Differences

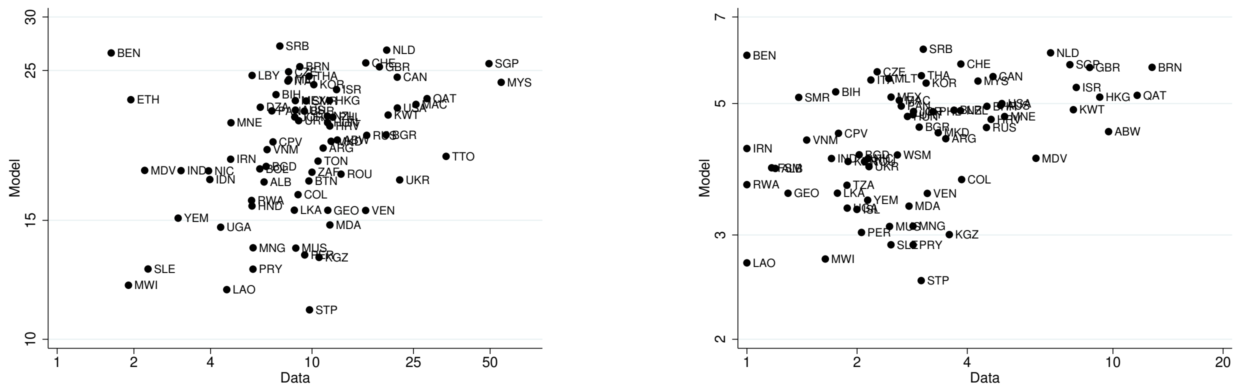
Our results in Table 1 shows no differential impacts of monitoring costs across sectoral outcomes, notably relative average size and sectoral TFP. This is because changes in sector specific factors, such as sectoral differences in exogenous productivity z_i, entry costs, and investment costs do not interact with monitoring technology. As a consequence, changes in m have proportionate effects across sectors. Here we briefly discuss how assuming sector-specific values for investment success q and monitoring costs m in our model could generate non-proportional impacts across sectors, focusing on equations (12) and (16) .

We start by considering sector-specific probabilities of investment success q. Data on employer firms from Business Dynamics Statistics (2007) suggests survival rates of firms one year after entry are 5.6 percent higher in services than in manufacturing.[14] Holding all parameters fixed and assuming the value of q is 5.6 percent higher in services than in manufacturing, changes in m can generate about a one percent larger drop in average size and TFP in services. This suggests our quantitative results miss little by abstracting from sectoral differences in q.

We now consider sectoral differences in the cost of monitoring, m. This exercise is more speculative, as there is no clear evidence to discipline differences in m across sectors. Sector-specific m has the potential to generate more substantial deviations from our benchmark results. For instance, if we assume bank monitoring technology in services is twice the value in manufacturing ($m_S = 2 \cdot m_M$), and then increase m proportionately in both sectors to generate an aggregate gross borrowing rate equal to 1.25 times the U.S. value, average firm size in manufacturing and services falls by 50 and 44 percent, while sectoral TFP falls by 23 and 29 percent. While the larger TFP drop in services is consistent with the larger cross-country differences in service-sector TFP observed by Buera et al. (2011) and others, the smaller impact on average size in services is not consistent with the data presented in Section 2, which suggests no statistically different impact on average size between sectors. If

[14] This data is not ideal, as it excludes nonemployer firms. Nonetheless, it gives us a ballpark estimate of survival differences to consider.

Figure 8: Establishment Size



(a) Manufacturing

(b) Services

Notes: All variables are shown in log scale. See the text for the definition of variables and sources.

anything, average size seems to be more impacted in services than in manufacturing.

As new sector-specific data on financial development becomes available in the future, our framework is flexible enough to allow for these and other sectoral differences.

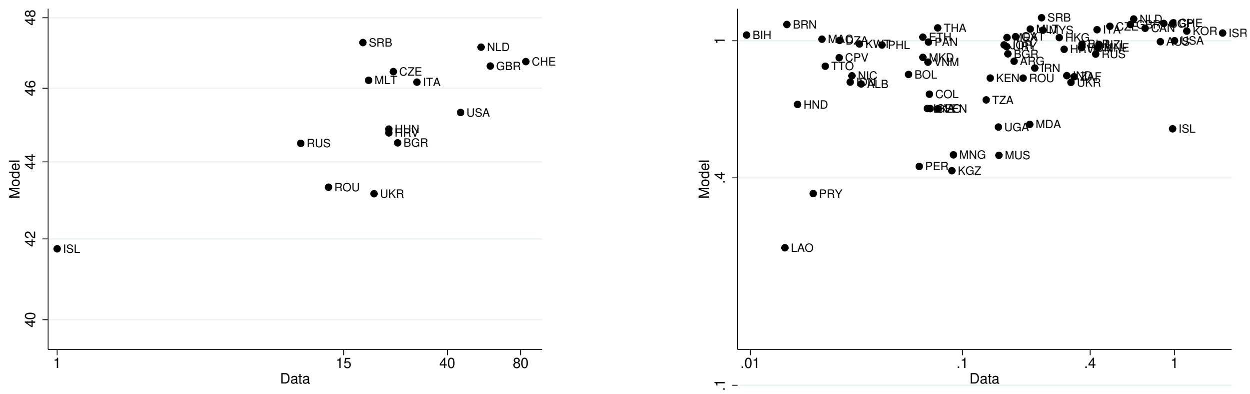
4.3 Cross-Country Exercise

The results in Section 4.2 show the impact of financial frictions on firm size, investment spending, and TFP due to variation in borrowing rates. We now evaluate more closely the country-specific predictions of the model against the data. We choose monitoring costs m to generate the country-specific aggregate gross borrowing rates documented in Section 2, while keeping all other parameters equal to their benchmark values. We then look at how differences in borrowing rates in the model can account for variation in firm size, investment, and TFP observed in the data. Specifically, we evaluate the model counterparts to the figures in Section 2. The range of m is between 9% of the benchmark U.S. level and 42 times the benchmark level.[15]

Figures 8 through 10 illustrate how our model-generated outcomes compare to the data

[15] Note that the calibrated model can not generate aggregate borrowing rates more than 1.27 times the U.S. rate. As m gets very high, loans for risky investment become insignificant relative to loans to finance entry costs. As a result, the aggregate rate no longer increases with m.

Figure 9: Employment Share of Large Firms and R&D Intensity

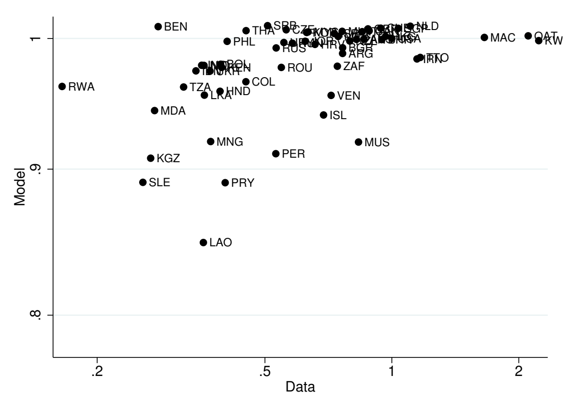


(a) Employment Share of Large Firms

(b) R&D Intensity

Notes: All variables are shown in log scale. See the text for the definition of variables and sources.

Figure 10: Aggregate TFP



Notes: All variables are shown in log scale. See the text for the definition of variables and sources.

when monitoring costs m are chosen for each country to generate observed aggregate borrowing rates. Figure 8a plots the relationship between average firm size in manufacturing across countries implied by the model and from the data, and Figure 8b shows the same relationship for services. There is a strong correlation between the model prediction for average size and the data in both sectors. Comparing the variation in logged outcomes from the model to that in the data, Figure 8 suggests variation in monitoring costs can account for 32 percent of the cross-country variation in average size in manufacturing and 38 percent in services. Figure 9a shows the employment share of large firms generated by the model is highly correlated with observed shares, although the model-generated shares only capture 4 percent of the observed cross-country variation. This is not overly surprising since we are accounting only for differences in financial development and abstract from labour market institutions which can have a first-order impact on the employment share of large firms. Figure 9b plots the relationship between the model-generated investment ratio and the R&D to GDP ratio reported in the data, where all values are relative to the U.S. Again there is a strong correlation between the model and the data (here by construction), with 25 percent of the variation in the data accounted for by borrowing rates. Finally, Figure 10 compares TFP from the model and the data. Here there is again a strong correlation between the model and the data, but the impact of monitoring costs on TFP implied by the model is not large enough to explain the large productivity differences across countries, accounting for 7 percent of the cross-country variation in TFP. We note that if α were assumed to be equal to $2/3$, the impact of monitoring costs on TFP implied by the model would account for a higher 12 percent of the observed variation.

5 Conclusion

There is now a large literature that studies the impact of financial frictions for understanding cross-country income and productivity differences. We contribute to this literature by documenting that financial development is associated with low borrowing costs, high investment in R&D, and large average firm size in all sectors. To account for these facts, we build a two sector model with heterogeneous entrepreneurs who invest in the productivity of their firms at entry, and where optimal investment is constrained by the extent of borrowing rates stemming from high monitoring costs in under-developed financial markets. The model we present is tractable and makes analytical predictions for the impact of financial development on aggregate borrowing rates, investment, and productivity that is consistent with the evidence we document. Calibrating the model to U.S. data, we find the quantitative impact of high borrowing costs is large relative to the existing literature. Specifically, differences in borrowing rates can account for much of the cross-country variation in investment and average firm size, and can account for a 30-45 percent drop in TFP.

Much of the work that examines the macro implications of financial frictions focus on entrepreneur differences in access to capital coming from collateral constraints, which affect both selection into entrepreneurship and the scale of those firms. While these models imply an inefficient allocation of resources across firms, their quantitative impacts depend on the persistence of firm-level productivity, which affects an entrepreneur's incentive to self-finance. Our model complements the quantitative findings of this literature by highlighting the importance high borrowing rates can have on start-up investment and entry. We show that the impact of financial frictions can be substantial even when incumbent entrepreneurs can eventually avoid high borrowing costs by self-financing, and serves to amplify the quantitative impacts found in the literature.

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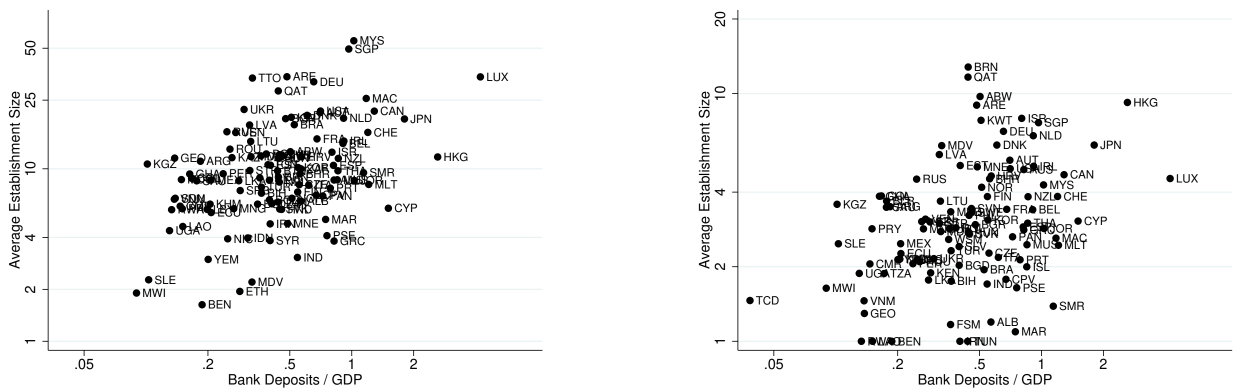
Figure 11: Establishment Size and Bank Deposits to GDP



(a) Manufacturing (b) Services

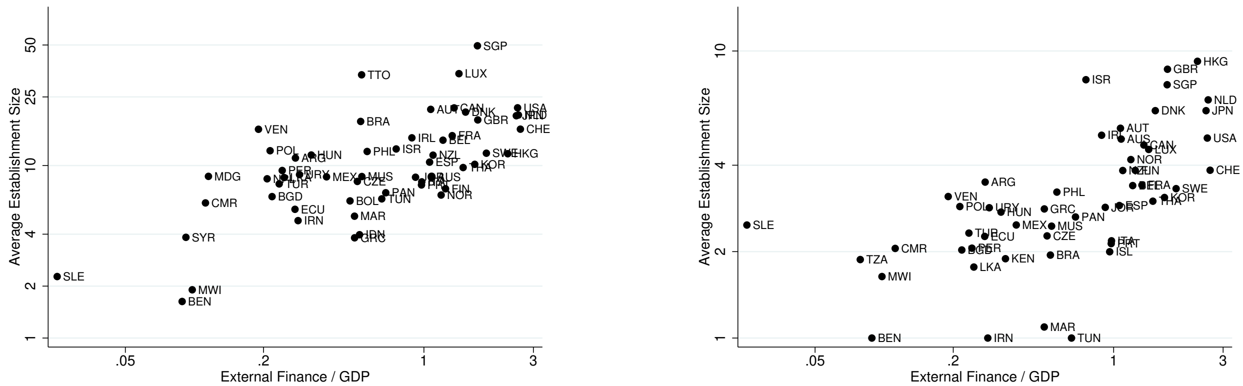
Notes: All variables are logged. See the text for the definition of variables and sources. Coefficients (standard errors) from OLS regressions are (a) 0.41 (0.08) and (b) 0.28 (0.06).

Appendix

A Other Measures of Financial Development

Here we show the cross-country relationships between borrowing rates, sectoral average firm size, the share of employment in large firms, and aggregate R&D intensity are robust to replacing borrowing rates with two commonly-used proxies for financial development – external finance and bank deposits, both measured relative to GDP. As in Section 2, the elasticity of average firm size with respect to each proxy seems to differ across sectors in Figures 11 and 12. But the ratio of average size in manufacturing relative to that in services has no statistically significant relationship to either proxy (as is the case with respect to borrowing rates), as shown in Figure 13. While the employment share of large firms is higher in economies with more external finance, Figure 14a shows no systematic relationship between the large firm employment share and bank deposits.

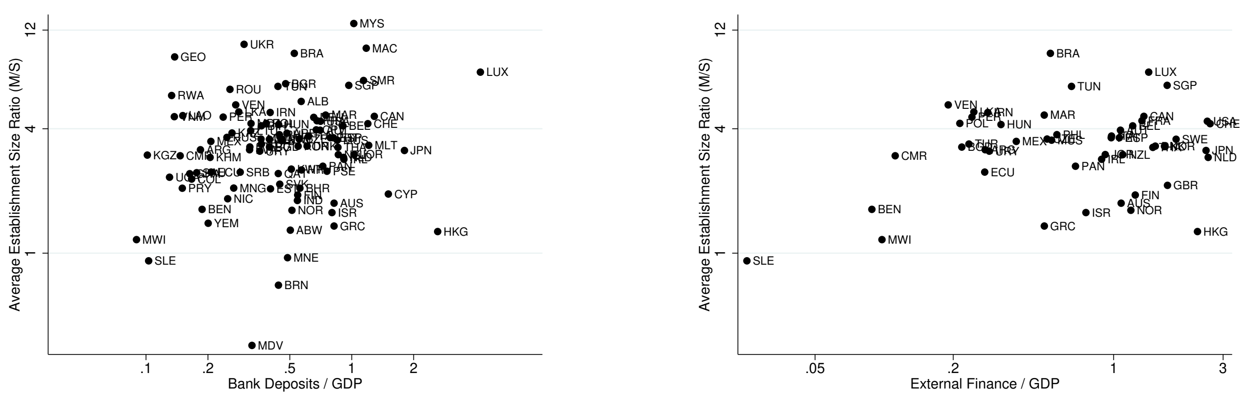
Figure 12: Establishment Size and External Finance to GDP



(a) Manufacturing (b) Services

Notes: All variables are logged. See the text for the definition of variables and sources. Coefficients (standard errors) from OLS regressions are (a) 0.42 (0.06) and (b) 0.33 (0.06).

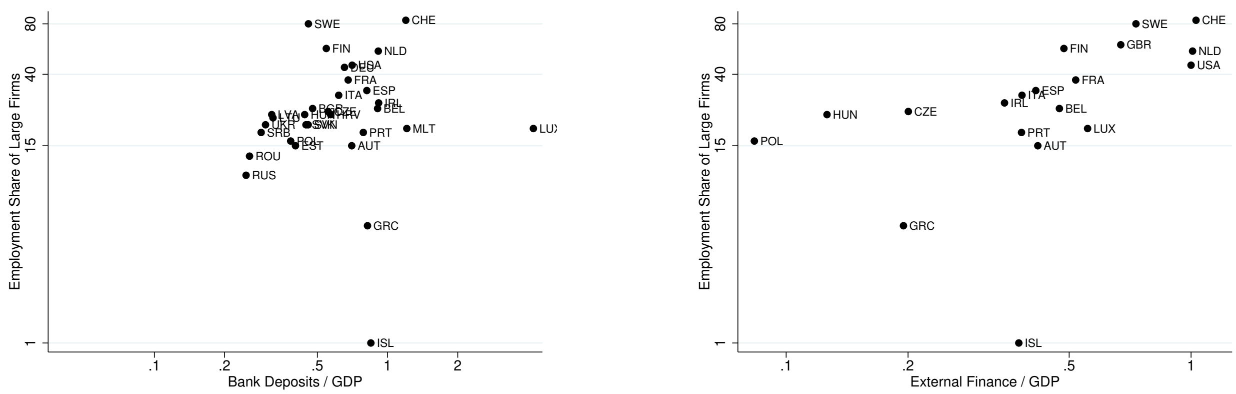
Figure 13: Relative Average Size (M/S), Bank Deposits, and External Finance



(a) Bank Deposits to GDP (b) External Finance to GDP

Notes: All variables are logged. See the text for the definition of variables and sources. Coefficients (standard errors) from OLS regressions are (a) 0.12 (0.09) and (b) 0.11 (0.08).

Figure 14: Employment Share of Large Firms, Bank Deposits, and External Finance

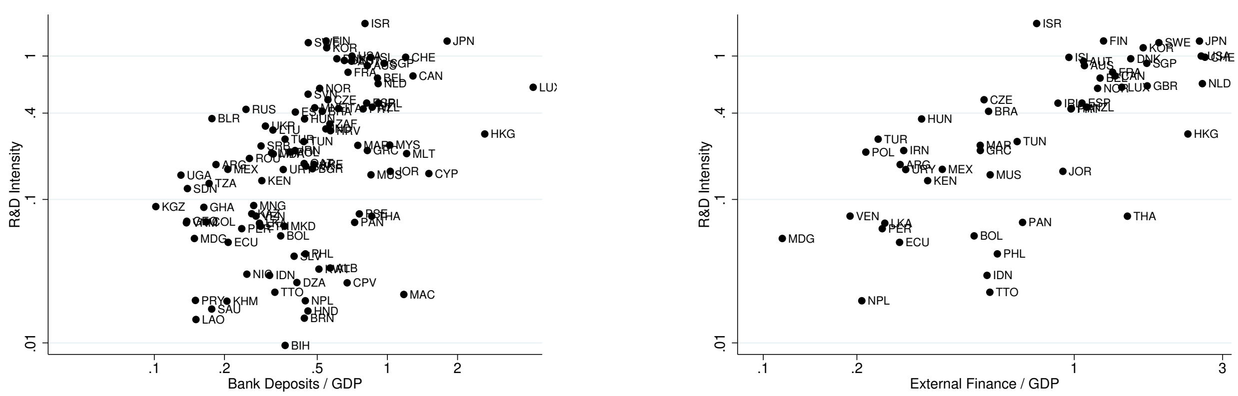


(a) Bank Deposits to GDP

(b) External Finance to GDP

Notes: All variables are logged. See the text for the definition of variables and sources. Coefficients (standard errors) from OLS regressions are (a) 0.10 (0.20) and (b) 0.72 (0.24).

Figure 15: R&D Intensity, Bank Deposits, and External Finance



(a) Bank Deposits to GDP

(b) External Finance to GDP

Notes: All variables are logged. See the text for the definition of variables and sources. Coefficients (standard errors) from OLS regressions are (a) 0.86 (0.14) and (b) 0.94 (0.13).

B Allowing for Life-Cycle Growth

Here we extend the model developed in Section 3 to allow for endogenous productivity growth over the life-cycle of a firm. We now change notation slightly to let $\hat{A}_0$ denote the pre-investment productivity of an entrant, A_0 to denote productivity after successful investment at entry, and A to denote productivity for producers after entry. After entry-investment, and in each period thereafter, a firm can choose to increase its productivity for the subsequent period by a factor x by incurring the following cost (in terms of goods);

$$wc_{X,i}\frac{A}{(A_0/\hat{A}_0)}x^{\theta}, \tag{19}$$

where $c_{X,i} > 0$, $\theta > 1$, A denotes a firm's current productivity, and $x \cdot A$ is a firm's next-period productivity. The cost of improving productivity is increasing in an entrepreneur's ability $\hat{A}_0$ and in the magnitude of previous life-cycle productivity growth, but independent of a firm's initial productivity improvement at entry. Note our specification of the cost of improving productivity is a deterministic version of that used in Atkeson and Burstein (2010). In each period, a firm's operating profits (previously equation 5) can now be expressed as a function of x, conditional on A_{-1};

$$\pi_i(x \mid A_{-1}) = xA_{-1}z_iP_i^{\frac{1}{1-\alpha}}(1-\alpha)\left(\frac{\alpha}{w}\right)^{\frac{\alpha}{1-\alpha}}. \tag{20}$$

In each period after production, a firm chooses x to solve the following problem;

$$\max_x \quad -wc_{X,i}\frac{A}{(A_0/\hat{A}_0)}x^{\theta} - x \cdot wc_{x,i}\frac{A}{(A_0/\hat{A}_0)}(x')^{\theta}\left(\frac{1-\lambda}{1+r-x'(1-\lambda)}\right)$$

$$+\pi_i(x \mid A)\left(\frac{1-\lambda}{1+r-x'(1-\lambda)}\right),$$

where x' denotes future choices of x and the large bracketed terms reflect the fact that both future expected discounted productivity investments and operating profits scale up with a firm's current choice of x. The solution to this problem can be characterized in the following way, taking into account that the firm will choose the same x each period in a stationary equilibrium;

$$wc_{X,i}\frac{A}{(A_0/\hat{A}_0)_i}x_i^\theta = \pi_i(x_i \mid A)\frac{1-\lambda}{\theta(1+r)-(\theta-1)x_i(1-\lambda)}. \tag{21}$$

For an equilibrium to exist, we require parameter values to be such that firms choose $x_i < \left(\frac{\theta}{\theta-1}\right)\left(\frac{1+r}{1-\lambda}\right)$. We note two features implied by (21). First, x_i is independent of $A/(A_0/\hat{A}_0)_i$, implying that all firms within a sector grow at the same rate. Second, the current cost of investment in future productivity is always less than current profit. To see this, we rearrange (21) to express investment as a fraction of current operating profits;

$$\frac{wc_{X,i}Ax_i^\theta}{\pi_i(A)(A_0/\hat{A}_0)} = \frac{x_i(1-\lambda)}{\theta(1+r)-(\theta-1)x_i(1-\lambda)} \quad \in \left(\frac{1-\lambda}{\theta(r+\lambda)+1-\lambda},\ \frac{1-\lambda}{\theta\lambda+1-\lambda}\right)$$

The above result implies that if the borrowing rate for this investment were at all higher than the risk-free rate (adjusted for the probability of exit), a firm would always choose to self-finance. Of course in the context of the above extension, there is no justification for a borrowing rate higher than the risk-free rate. But if we were to add uncertainty to realized productivity growth outcomes, combined with monitoring costs associated with bad draws, firms would avoid the higher associated borrowing rates by financing investment out of current profits.

We now continue to solve this extended model to show that the qualitative relationships implied by the benchmark model in Section 3 still hold. Denote the initial productivity of an entrant after successful entry-investment as A_0. Entrants then choose initial productivity to maximize $V_i(A_0 \mid \hat{A}_0)$, defined as follows;

$$V_i(A_0 \mid \hat{A}_0) = -q \cdot wc_{0,i}\hat{A}_0(A_0/\hat{A}_0)^\phi(1+r_b)$$

$$+q\pi_i(A_0)\left(\frac{\theta(1+r)}{\theta(1+r)-(\theta-1)x_i(1-\lambda)}\right) + \left(\frac{1-q}{1+r}\right)V_i(A_0' \mid \hat{A}_0).$$

The solution to this problem is;

$$w c_{0,i} \hat{A}_0 (A_0/\hat{A}_0)^{\phi} = \frac{\pi_i(A_0)}{\phi + (\phi+\gamma)m(1-q)} \left(\frac{q\theta(1+r)}{\theta(1+r) - (\theta-1)x_i(1-\lambda)} \right). \tag{22}$$

We can now express the value of an entrant, given $\hat{A}_0$, as;

$$V_i(\hat{A}_0) = \frac{\pi_i(A_0(\hat{A}_0))}{r+q} \left(\frac{q\theta(1+r)^2}{\theta(1+r) - (\theta-1)x_i(1-\lambda)} \right) \left(\frac{\phi - 1 + (\phi - 1 + \gamma)m(1-q)}{\phi + (\phi+\gamma)m(1-q)} \right), \tag{23}$$

with x_i given by (21) and A_0 given by (22).

Using labor market clearing, operating profits as a function of A can now be expressed as;

$$\pi(A) = w \left(\frac{1-\alpha}{\alpha} \right) \frac{A \cdot (L_i/N_i)}{\mathbb{E}(A_i)},$$

where $\mathbb{E}(A_i)$ denotes average A across firms in sector i;

$$\mathbb{E}(A_i) = \mathbb{E}(\hat{A}_0)(A_0/\hat{A}_0)_i \left(\frac{\lambda}{1 - x_i(1-\lambda)} \right).$$

Using the free entry condition, we obtain average firm size (across all firms) in sector i;

$$size_i = \psi c_{E,i} \left(\frac{\theta(1+r) - (\theta-1)x_i(1-\lambda)}{1 - x_i(1-\lambda)} \right) \cdot \left(\frac{\phi + (\phi+\gamma)m(1-q)}{\phi - 1 + (\phi - 1 + \gamma)m(1-q)} \right), \tag{24}$$

$$\psi \equiv \frac{\alpha\lambda(r+q)}{\theta(1+r)^2(1-\alpha)[\lambda + (1-\lambda)q]}.$$

Optimal initial productivity can be expressed as;

$$(A_0/\hat{A}_0)_i^{\phi} = \frac{c_{E,i}(r+q)}{c_{0,i}(1+r)\mathbb{E}(\hat{A}_0)\left[\phi - 1 + (\phi+\gamma-1)m(1-q)\right]}, \tag{25}$$

which remains unchanged from equation (13). And optimal life-cycle growth x can be characterized in the following way;

$$x_i^{\theta-1} = \frac{c_{E,i}}{c_{X,i} q \theta (1+r) \mathbb{E}(\hat{A}_0)} \left(\frac{r+q}{1+r} \right) \cdot \left(\frac{\phi + (\phi+\gamma) m (1-q)}{\phi - 1 + (\phi - 1 + \gamma) m (1-q)} \right). \tag{26}$$

From the last bracketed term in (26), it is clear that x_i is decreasing in monitoring costs m, implying economies with high borrowing rates due to high monitoring costs will feature slower life-cycle productivity growth. Further, the impact on x from higher m is proportionately the same across sectors. As in the model from Section 3, a higher m has a negative impact on initial productivity improvements at entry (25). Given the negative relationship between m and x, it is clear from equation (24) that average size is still decreasing in m. Our results here differ from those in Section 3 in one respect: here it is possible for m to have a differential impact across sectors on both average size and sectoral TFP. If one sector has a higher x, an increase in m will decrease average size by a larger proportion. To see the impact on sectoral TFP, we first derive the following expression for TFP_i as a function of x_i;

$$TFP_i \propto \left(\frac{\mathbb{E}(A_i)}{size_i} \right)^{1-\alpha} \propto \left(\frac{1}{\theta(1+r) - (\theta-1) x_i (1-\lambda)} \right)^{1-\alpha}.$$

Given the proportional impact of m on x in each sector, this expression shows a higher m will reduce TFP more in the sector with higher life-cycle growth. At the same time, given the low observed growth rates in the U.S. ($x = 1.05$ for U.S. manufacturing firms, according to Hsieh and Klenow (2014)), and assuming that x can only drop to as low as 1 (0% growth), any differential impact on TFP across sectors must be quantitatively very small.

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