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Shocks, Financial Dependence, and Efficiency: Evidence from U.S. and Canadian Industries

Marcello Estevão and Tiago Severo

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Shocks, Financial Dependence, and Efficiency: Evidence from U.S. and Canadian Industries

Prepared by Marcello Estevão and Tiago Severo[1]

Authorized for distribution by Gian Maria Milesi-Ferretti

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Abstract

The paper investigates how changes in industries' funding costs affect total factor productivity (TFP) growth. Based on panel regressions using 31 U.S. and Canadian industries between 1991 and 2007, and using industries' dependence on external funding as an identification mechanism, we show that increases in the cost of funds have a statistically significant and economically meaningful negative impact on TFP growth. This effect is, however, non-monotonic across sectors with different degrees of dependence on external finance. Our findings cannot be explained by either increasing returns to scale or factor hoarding, as results are not sensitive to controlling for industry size and our calculations account for changes in factor utilization. The paper presents a theoretical model that produces the observed non-monotonic effect of financial shocks on TFP growth and suggests that financial shocks distort the allocation of factors across firms even within an industry, thus reducing TFP growth.

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Authors' E-Mail Addresses: mestevao@imf.org, tsevero@imf.org

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I. INTRODUCTION

How do financial shocks propagate through the real economy? This question is of central importance for economists and policymakers. The recent global financial crisis and the ensuing drop in production and employment across various countries reinforced the need to address the topic. Unfortunately, traditional models of economic fluctuations have, in general, neglected the role of finance in determining real macroeconomic variables. In some of these frameworks, financial markets act as propagation mechanisms to underlying shocks (Bernanke and Gertler, 1989), but the main source of fluctuations are changes to fundamentals, with particular emphasis to technology. Such technological shocks have been incorporated into most macroeconomic models as changes in total factor productivity (TFP).

From an academic point of view, understanding the behavior of TFP is central for both macroeconomics and the theory of economic growth. The real business cycle literature initiated by Kydland and Prescott (1982), a workhorse for the analysis of cyclical fluctuations in modern macroeconomics, is founded upon the notion that technological shocks, which directly affect aggregate TFP, are the main source of short-run fluctuations in the economy. Focusing on more extreme fluctuations, Kehoe and Prescott (2007) compile numerous studies and conclude that the evolution of aggregate TFP is a crucial mechanism behind international episodes of economic depression. Turning to the long run, Solow's growth model predicts that economic growth is directly linked to technological progress, which is captured as improvements in aggregate TFP.

Despite the importance of cyclical variations in TFP, the academic literature usually treats it as stochastic and exogenous, often without testing the validity of these hypotheses. In a recent paper, Chari et al. (2007) provide a theoretical avenue for the comprehension of the cyclical behavior of aggregate TFP.[2] According to the authors, distortions introduced by taxes or other sources of frictions can be represented as wedges in agents' optimality conditions. In some contexts, changes in the wedges are isomorphic to fluctuations in aggregate TFP in a standard frictionless neoclassical model. Regarding the role of financial shocks, Chari et al. (2007) construct an example of an economy with credit frictions and argue that shocks to the frictions in the distorted economy are equivalent to shocks to aggregate TFP in a frictionless world. From an empirical perspective, though, the relation between productivity and financial shocks is hard to establish.

In the present paper, we develop a stylized model in the spirit of Chari et al. (2007) with firms distributed across different sectors. According to calibrations of the model, increases

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[2] The endogenous growth theory—e.g., as discussed by Aghion and Howitt (1992)—explicitly models the behavior of TFP, but it is more focused on long-run phenomena related to economic growth.

in the cost of funds reduce sectoral TFP growth. However, the predicted effect varies non-monotonically with each sector's dependence on external funds, which is assumed exogenous. That is, TFP is affected the most for those industries with intermediary levels of dependence on finance, whereas it is affected the least for sectors in the extreme – the ones fully dependent on external funds and the ones that do not need them at all. Hence, in our framework sectoral dependence on external finance appears as a useful identifying device.

This non-monotonic impact of financial shocks on TFP is a novel result. It is in contrast to the liquidationist view of financial crisis popularized by Schumpeter and Hayek. It is also contrary to the predictions of the reverse liquidationist approach of Caballero and Hammour (1994) and Caballero and Hammour (2005). Moreover, it cannot be easily reconciled with models of endogenous productivity growth as in Aghion and Howitt (1992). The link between sectoral productivity and financial shocks in our model results from the impact of the latter on the scale of operation of individual firms within each sector. Specifically, our model suggests that increases in average corporate bond yields or in the cost of issuing equity are followed by greater cross-firm dispersion in financial frictions. Such increased dispersion induces inefficient changes in the relative magnitudes of individuals firms, ultimately impacting aggregate TFP.

That financial shocks have the smallest impact on productivity for industries that do not depend on external funds is naturally understood. What is interesting is that this effect is equally small for a sector that is fully financed by borrowed funds. The key element here is to realize that, because firm-level TFP is assumed exogenous, financial conditions can only affect aggregate productivity to the extent that they change the *relative* scale of operation of firms with different levels of efficiency. And despite the *absolute* scale of firms in a fully dependent sector being affected the most by financial shocks, their *relative* sizes is preserved, leaving sectoral TFP unchanged. Indeed, the efficiency of sectors with intermediary degrees of dependence on finance is hurt more since the relative scale of their firms is highly sensitive to shocks emanating from financial markets.

With this framework in mind, the paper sets up a test for the effect of financial shocks on TFP growth. Using panel data for manufacturing industries in the United States and Canada between 1991 and 2007, we show that increases in the cost of capital adversely affect the way they combine inputs in the production process, i.e. total factor productivity. More specifically, we follow the lead of Rajan and Zingales (1998)—henceforth RZ—and rank the manufacturing industries according to their dependence on external finance. Then, we analyze the differential effect of changes in the cost of funds on sectoral TFP growth across industries with different dependence on borrowed funds, uncovering a u-shaped pattern as predicted by the model. This is especially surprising given that we control for changes in factor utilization, substantially weakening the importance of factor hoarding as a potential explanation for our finding. Additionally, we notice that the effect of the cost of funds on output is non-monotonic as well due to the effects in TFP, since the same is not true for other inputs: labor, capital, and capacity utilization.

Our methodology is based on the interaction of the yields on corporate bonds with a sectoral index of dependence on external finance constructed by Rajan and Zingales and using the resulting series as an explanatory variable in panel regressions where sectoral TFP growth is the dependent variable. By focusing on sectoral TFP we are able to better identify the effects of financial shocks on aggregate productivity more generally. The underlying assumption is that dependence on external finance is related to characteristics of the production process and the market structure in which industries operate, being reasonably exogenous relative to TFP or inputs. This is indeed the basic principle behind the original work of Rajan and Zingales, which has also been adopted by several authors. The sign and magnitude of the estimated coefficient on the interaction variable serve as a test for the effect of financial shocks on productivity. Time dummies are included in order to control for any events that, over time, might affect TFP homogenously across sectors. We also include dummies to capture sector fixed effects. The regressions confirm that interest rates have a statistically significant and economically meaningful negative effect on TFP growth. In the baseline specification, we estimate that an increase of 100 basis points in corporate bond yields brings TFP growth in sectors with an average degree of dependence on external finance roughly 0.65 percentage points below TFP growth in a benchmark sector that either does not depend or is fully dependent on external funding. This is roughly 40 percent of the average growth rate of sectoral TFP in our sample.

In order to check the robustness of our findings, we construct a measure of the cost of issuing equity instead of debt, which varies both over time and across industries. More specifically, we estimate industry specific betas on the market portfolio and interact them with a proxy for the expected return on the market—its dividend yield. According to the CAPM, this provides a measure of the expected return on equity at the industry level, thus providing a benchmark for corporations' cost of capital. The negative link between TFP growth and the cost of funds is even stronger in this case. A one-standard deviation increase in our measure for the cost of equity reduces annual TFP growth in sectors with an average degree of dependence on external finance by 1.29 percentage point vis-à-vis sectors in the extreme.

Our results contribute to the understanding of how acute financial crises may affect output, factor utilization, and productivity. Severe crises undermine the financial system, with negative consequences for the allocation of capital and production in the economy. Given this potential link between financial shocks and efficiency, one wonders which dimensions are distorted most. In particular, in the aftermath of crises, should governments be concerned about the inadequate expansion of particular industries in the economy, or should they be concerned about important misallocations of factors across firms even within a sector? Based on our theoretical framework and especially on the empirical results, we are inclined to suggest that there might be relevant distortions across firms within each manufacturing industry.

The present paper also contributes to a recent wave of academic and applied research focused on better accounting for the importance of financial markets on the macroeconomic performance of countries. This new agenda is crystallized in the push for formally incorporating relatively complex financial sectors in DSGE models, in order to evaluate the costs and benefits of various policies. Our empirical and theoretical results may be of help in this respect. First, they suggest that models which treat TFP as an exogenous random variable may not be able to properly account for the real consequences of financial disruptions. Second, our findings suggest that the inclusion of cross-firm heterogeneity in the access to finance could be an important tool for those models to generate interesting dynamics and co-movement between real and financial variables.

The remainder of the paper is organized as follows. Section 2 presents our stylized model and discusses alternative theories relating TFP to the cost of funds, underlying the main differences between their predictions. Section 3 describes how we obtain our data for TFP and other variables used in the regressions. Section 4 presents the main empirical results and various robustness checks. Section 5 focus only on the U.S. industries and presents an alternative measure of the cost of funds, based on returns on equity. Sections 6 and 7 have some discussion and conclusion. The appendix contains all figures and tables as well as a description of calibration exercises.

II. Theory

A. Model Relating TFP and Financial Shocks

This section develops a simple model of monopolistic competition and heterogeneous dependence on external finance in order to set the stage for the analysis of financial shocks and TFP. Our method follows the research line in Chari et al. (2007), Melitz (2003), and Hsieh and Klenow (2009). The main innovation is the explicit treatment—albeit in a reduced form—of differences in the degree of dependence on external finance across industries.

Consider an economy with S industries that produce goods which are imperfect substitutes. For simplicity, we assume that each industry s is composed by N firms, where N is big. The uniform dispersion of firms across industries is immaterial for our results but saves notation. We assume that each individual firm has some monopoly power in the market for its product, since goods are not perfect substitutes even within a sector. Industry output Y_s is the result of a CES aggregator of firm specific output y_{si} as follows:

$$Y_s = \left[\sum_{i=1}^{N} y_{si}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

Firms last for two periods only, and have no endowment or any kind of resources. In the first period, they hire physical capital and labor in factors markets, borrowing funds to do so if necessary. At the beginning of the second period, individual firms face an exogenous productivity shock. Conditional on being productive, they execute their production plans, paying factor owners and liquidating their debts in the end of period two, before shutting down. Production is undertaken using a Cobb-Douglas technology represented by:

$$y_{si} = A_{si} {k_{si}}^{\alpha_s} {l_{si}}^{1-\alpha_s}$$

From a first period's perspective, the exogenous productivity parameter A_{si} is stochastic and independently distributed across firms: it is equal to $\tilde{A}_{si} > 0$ with probability q_{si} and equals 0 otherwise. We allow q_{si} as well as the parameter $\tilde{A}_{si}$ to vary across firms and sectors. The only restriction we impose is that, for each sector, these two parameters are at least weakly negatively correlated in the cross-section. This ensures that, other things equal, riskier activities (the ones with lower probability of succeeding) tend to have larger productivity conditional on them being successful.

We assume that, at every period, a fraction θ_s of the production costs of firm i in sector s

$$w_{si} l_{si} + r_{si} k_{si}$$

has to be paid at the time inputs are hired and before the realization of the productivity shock. This type of cash-in-advance constraint has been used before in the literature.[3] In the present context, it is meant to capture firms' need to raise working capital in order to produce a good. It can also be seen as a reduced-form way of capturing the fact that investment and production costs have to be paid during different stages of the production process. θ_s varies across sectors, but it is identical for firms within a sector. Implicitly, this approach postulates that working capital needs are exogenously determined by the industry where firms operate. Such an assumption is in line with the claims in RZ's construction of their index of dependence on external finance, which will be examined in detail in the next section.

External funds are raised in competitive financial markets. Because firms have to borrow before the realization of the technological shock, lenders face firm-specific credit risk: if a firm turns out to be unproductive, it will shut down and default on its financial commitments. The cost of funds faced by firm i in sector s is denoted by τ_{si}. If $\tau > 1$ represents the average

[3] See Neumeyer and Perry (2004) for example.

cost of funds in financial markets[4], and assuming that the risk-neutral lenders can reallocate funds freely across firms and sectors, we have:

$$\tau_{si} = \beta_{si}\tau$$

where

$$\beta_{si} = \frac{1}{q_{si}\sum_{j=1}^{SN}\frac{1}{SNq_{sj}}}$$

Firms rent capital and labor in competitive markets, before knowing the realization of their productivity shock. The rental rates of k and l faced by firm i in sector s are r_{si} and w_{si} respectively. Firms sign non-contingent contracts with risk neutral factor owners, that is, the contractual rental rates to be paid to the factors are defined ex-ante. A fraction θ_s of these payments is riskless, since it is paid up-front with borrowed funds. The remaining fraction, though, is risky due to uncertainty about productivity. Hence, for each firm i and each sector s, the following equilibrium conditions hold:

$$w_{si} = \frac{w}{\theta_s + (1-\theta_s)q_{si}}$$

$$r_{si} = \frac{r}{\theta_s + (1-\theta_s)q_{si}}$$

where w and r are the riskless opportunity cost for labor and capital respectively.

Finally, we assume that firms do not liaise and redistribute funds or inputs among themselves outside capital markets or the markets for factors. Otherwise, it could be optimal for the least risky firm to be the only borrower of external funds, which eliminates the role of financial frictions. This assumption is a simple way of incorporating microstructure failures, like incompleteness of contracts for instance.

The possibility of default by unproductive firms effectively empowers them with limited liability. Under those conditions, the problem of an individual firm in sector s can be written as:

$$maximize_{p,k,l}\{max\{E[p_{si}y_{si} - (1-\theta_s)(w_{si}l_{si} + r_{si}k_{si}) - \theta_s\tau_{si}(w_{si}l_{si} + r_{si}k_{si})], 0\}\}$$

subject to

[4] By hypothesis, we assume that such average is well defined. This will always be the case in a market economy provided preferences and endowments have the usual properties.

$$p_{si} = P_s \left(\frac{Y_s}{y_{si}}\right)^{\frac{1}{\sigma}}$$

where p_{si} is the firm-specific price, and where

$$P_s = \left[\sum_{i=1}^{N} p_{si}^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$$

denotes the sectoral price level.

As usual, the solution to this optimization problem is obtained assuming the individual firm takes the sectoral variables as independent from its own choices or the realization of its individual productivity. Combining that with the limited liability condition, the profit maximization for firm i in sector s can be rewritten as:

$$maximize \left\{E\left[P_s Y_s^{\frac{1}{\sigma}}\right]\left[\tilde{A}_{si} k_{si}{}^{\alpha_s} l_{si}{}^{1-\alpha_s}\right]^{\frac{\sigma-1}{\sigma}} - \big((1-\theta_s) + \theta_s \tau_{si}\big)(w_{si} l_{si} + r_{si} k_{si})\right\}$$

The solution to this maximization problem is characterized by:

$$\frac{k_{si}}{l_{si}} = \frac{\alpha_s}{1-\alpha_s}\frac{w}{r} \tag{1}$$

$$l_{si} = \left(\frac{\tilde{A}_{si}}{\tilde{A}_{sj}}\right)^{\sigma-1}\left[\frac{(1-\theta_s)+\theta_s\beta_{sj}\tau}{(1-\theta_s)q_{sj}+\theta_s}\right]^{\sigma} \Big/ \left[\frac{(1-\theta_s)+\theta_s\beta_{si}\tau}{(1-\theta_s)q_{si}+\theta_s}\right]^{\sigma} l_{sj} \tag{2}$$

Equation (1) shows that the capital-labor ratio is identical for all firms in a given industry, and is determined solely by the share of each input in production and their relative opportunity costs. Interestingly, the ratio should not be related to the parameter of dependence on external finance θ. Equation (2) indicates that the size of the labor force hired by firm *i* relative to its peer *j* depends on their individual TFPs (conditional on being productive), their risk profile (represented by *q* and β), the average cost of external funds τ and the industry's dependence on finance θ. Because capital-labor ratios are constant in each sector, the relative sizes of the labor force actually indicate the relative scale of operations of firms in the same industry – measured as the total inputs hired. This conclusion is an important piece to build our intuition for the relation between financial shocks and sectoral TFP, which is developed below.

In order to obtain an expression for TFP at the industry level, one can write an aggregate production function for industry s

$$Y_s = A_s K_s^{\alpha_s} {L_s}^{1-\alpha_s}$$

where

$$L_s = \sum_{i=1}^{N} l_{si}$$

and

$$K_s = \sum_{i=1}^{N} k_{si}$$

and where A_s is the industry's total factor productivity. This comes at no cost in terms of generality, since we have not imposed any restriction on the nature of A_s. Proposition 1 below shows how A_s depends on the true technological elements $\tilde{A}_{si}$ and the interaction between dependence on external finance and the average cost of funds across all firms. Let us establish some useful notation first.

Definition: *For each firm i in sector s, define γ_{si} as:*

$$\gamma_{si} = \left\{ \frac{\left(\tilde{A}_{si}\right)^{\sigma-1}}{\left[\frac{(1-\theta_s)+\theta_s\beta_{si}\tau}{(1-\theta_s)q_{si}+\theta_s}\right]^{\sigma}} \right\} \Bigg/ \sum_{j=1}^{N} \left\{ \frac{\left(\tilde{A}_{sj}\right)^{\sigma-1}}{\left[\frac{(1-\theta_s)+\theta_s\beta_{sj}\tau}{(1-\theta_s)q_{sj}+\theta_s}\right]^{\sigma}} \right\}$$

A simple manipulation of equation (2) shows that for every firm *i* in sector *s*, we have:

$$l_{si} = \gamma_{si} L_s \tag{3}$$

Moreover, considering that $\gamma_{si} > 0$ and

$$\sum_{i=1}^{N} \gamma_{si} = 1$$

we can interpret it as the scale of firm *i* relative to the industry where it operates.

Definition: *In any given period, define Ω_s as the set of firms in industry s that realize positive productivity.*

Noting that Ω_s itself is a random variable, we conclude that:

Proposition 1: *For any realization of Ω_s, the expression for total factor productivity in industry s is given by:*

$$A_s = \left[\sum_{i\in\Omega_s} \left(\gamma_{si}\tilde{A}_{si}\right)^{\frac{\sigma-1}{\sigma}} + \sum_{i\notin\Omega_s} (\gamma_{si}0)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} = \left[\sum_{i\in\Omega_s} \left(\gamma_{si}\tilde{A}_{si}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

Proof: *See the appendix.*

The expression for sectoral TFP resembles a weighted average of firm-specific TFP, where the weights are determined by each firm's productivity and cost of finance relative to their peers. Since individual TFP is assumed exogenous, the effect of shocks to τ on aggregate productivity must occur through a reshuffling of the weights. Hence, a change in the average cost of funds τ will affect aggregate TFP provided that firms with different levels of productivity change the scale of their operations relative to their competitors.

This connection between aggregate TFP and the overall cost of finance is independent of common changes in any given sector. Indeed, the model predicts that sectoral productivity will be irresponsive to changes in the cost of funds if all firms move in tandem. This will be the case under certain conditions:

Proposition 2: *For any realization of Ω_s,$\frac{\partial A_s}{\partial \tau} = 0$ if:*

i) q_{si} is identical for all $i \in \Omega_s$, or:
ii) $\theta_s = 1$, or:
iii) $\theta_s = 0$.

Proof: *See the appendix.*

If the risk profile is identical for all firms, changes in τ will increase the cost of financing uniformly across them, affecting their absolute sizes identically but leaving their relative scales unchanged. Hence aggregate TFP does not move. A similar phenomenon happens in sectors that are fully dependent on external finance, i.e. $\theta_s = 1$. Finally, the productivity of sectors that do not depend on external finance at all - $\theta_s = 0$ - shall not be affected by changes in τ.

It is hard to derive a closed-form expression for the impact of changes in the cost of funds on the aggregate TFP of sectors with intermediary levels of dependence on finance. However, a simple calibration of the model would shed light on how changes in the cost of funds affect the growth rate of TFP across sectors with different values of θ_s.[5] The qualitative effects are represented in Figure 1. In line with the results in proposition 2, the calibration shows that changes in the cost of funds have no effect on aggregate TFP either for sectors that fully depend on external finance or for sectors that do not depend on it at all. In fact, productivity is mostly negatively affected – in relative terms - for those industries with moderate values of θ_s. The U-shaped pattern displayed in that figure is robust to many different specifications for the parameters of the model. The only crucial hypothesis is that riskiness, represented by $1 - q_{si}$, is positively associated with the potential productivity of firms. If this condition is reversed, the representation becomes an inverted U-shape.

We now shed light on this calibration result as well as on results ii) and iii) in proposition 2. To build the intuition, consider the case of a planner who, after observing a realization of the productivity shocks, redistributes the resources hired by the ex-post productive firms within each sector. The planner's objective is to maximize sectoral output. That is, we consider a planner who reallocates labor and capital among the productive units in an industry to achieve production efficiency, disregarding the - by now sank - funding costs or relative prices of capital and labor. For any realization of Ω_s, the planner's problem becomes:

$$maximize_{k_{si},l_{si}} \left\{ \left[\sum_{i \in \Omega_s} \left(\tilde{A}_{si} {k_{si}^*}^{\alpha_s} {l_{si}^*}^{1-\alpha_s} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \right\}$$

subject to

$$\sum_{i \in \Omega_s} l_{si}^* \leq \sum_{i \in \Omega_s} l_{si}$$

and

$$\sum_{i \in \Omega_s} k_{si}^* \leq \sum_{i \in \Omega_s} k_{si}$$

The solution to this program features

$$\frac{k_{si}^*}{l_{si}^*} = \frac{K_s}{L_s} = \frac{\alpha_s}{1-\alpha_s} \frac{w}{r} \tag{4}$$

[5] The appendix contains details of the calibration.

for all $i \in \Omega_s$. Moreover, it is straightforward to verify that[6], for any $i \in \Omega_s$, the optimal relative scale of plants is given by:

$$l_{si}^* = \gamma^*{}_{si}\left(\sum_{i \in \Omega_s} l_{si}\right) \tag{5}$$

where

$$\gamma^*{}_{si} = \tilde{A}_{si}{}^{\sigma-1} / \sum_{j \in \Omega_s}\left(\tilde{A}_{sj}{}^{\sigma-1}\right) \tag{6}$$

Hence, a planner who cares solely about production efficiency allocates resources across firms based on their relative productivities only – equations (5) and (6). Individual firms operating in competitive markets, on the other hand, take into account not only their future productivity but also the cost of external funds when choosing the size of their operations – equations (2) and (3). Because firms cannot redistribute inputs or funds among themselves ex-post, they can never achieve production efficiency.[7] When the cost of funds increases, the importance of productivity as a guide for the market allocation diminishes relative to the importance of the cost of finance. This moves industries further away from the sectoral efficiency frontier, impacting aggregate TFP negatively. However, the magnitude of this effect depends on θ_s.

To comprehend this last point, we need to focus on the average cost of funds, ACF, for each firm *i* in sector *s*, and how it varies relative to other firms for different values of τ:

$$ACF_{si} = [(1 - \theta_s) + \theta_s \beta_{si} \tau]$$

For all firms in a sector that does not depend at all on external finance, the ACF is identical to 1 no matter τ. Hence, the final allocation mimics the social planner's choice. In a sector that fully depends on external finance, on the other hand, the ACF is, on average, the highest. However, the ACF for firm *i relative* to any other firm in the sector does not depend on τ. Hence, changes in the cost of finance will not affect the *relative* scales of firms, leaving aggregate productivity unchanged. For intermediary values of θ_s, though, changes in the cost of funds will have the widest impact on *relative* scales – since they will strongly affect the cross-section dispersion of ACF_{si} – inducing counterproductive reallocation of funds and hurting aggregate productivity the most.

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[6] The proof of this assertion follows the same steps in the proof of proposition 1.

[7] Another reason why firms do not achieve production efficiency is related to fact that they maximize profits in a context of monopolistic competition. This, however, bears no relation to financial shocks or dependence on external funds.

It is important to note that this intuition is valid as long as productivity is positively associated with riskiness. In this case, as the cost of funds increases, the increased dispersion in ACF will hurt more firms with lower probability of survival q_{si}, the ones with a larger $\tilde{A}_{si}$. Hence, for any realization of Ω_s, aggregate TFP will be smaller. If, on the other hand, the relationship between risk and productivity is negative, results would revert and the pattern depicted in Figure 1 would be an inverted U-shape instead. As discussed before, this second possibility is less appealing, since it requires a negative correlation between risk and "return".

In the empirical section of the paper, we test the relation between the cost of funds for corporations and the *growth* rate of TFP, not its level as presented in the model. However, in an environment where firm level TFP evolves exogenously – an assumption underlying this as well as the vast majority of models of firm behavior – the analysis presented above can be extended to the growth of productivity as well. If riskier activities tend to have higher productivity growth upon survival, the conclusions are exactly the same: financial shocks have a negative, u-shaped impact on aggregate productivity across sectors with different degrees of dependence on borrowed funds. The intuition is identical to the one discussed before, and it was confirmed by calibrations designed to capture the impact of shocks to τ on TFP growth.

Finally, it is important to emphasize that the analysis has focused exclusively on TFP and its connection to the cost of funds. This basic theoretical framework also has implications for the relation between financial shocks and other variables like production, factor accumulation, and profits. It is easy to consider these other dimensions from a theoretical perspective, but identifying them empirically is extremely hard. The problem is that financial shocks also tend to affected aggregate demand, which has implications for these very same variables. TFP, on the other hand, should be relatively immune to such variations, at least from the perspective of a standard neoclassical model. Moreover, our model is extremely simple and is not meant to fully capture the nature of the relation between the cost of finance and other variables like output, capital and labor. Its purpose is to provide a simple analytical framework that highlights some basic mechanisms linking the variables under consideration.

B. Creative Destruction and the "Cleansing" Effect

An alternative framework relating financial shocks and TFP is based on creative destruction theories. This liquidationist view, popularized by Hayek and Schumpeter among others,[8] postulates that crises are times of "cleansing" in the sense that outdated and unproductive plants and technologies are eliminated from the productive system and substituted for more efficient structures (Caballero and Hammour, 1994). In the context of our analysis, this

[8] See De Long (1990).

theory predicts that financial shocks, by increasing the cost of funds, accelerate the death of old and unproductive firms, raising average productivity for industries. Additionally, this effect should be more pronounced for sectors that depend more on external finance, since their death rate of outdated plants should be higher.

Economists have not reached an agreement with respect to the validity of the "cleansing-effect" hypothesis, especially during recessions. Recessions and crises can impose frictions in the system, which impair the process of restructuring necessary to weed out unproductive units. For example, a reduction in the supply of finance might slow down mergers and acquisitions. According to Caballero and Hamour (2005): "*The common inference that increased liquidations during crises result in increased restructuring is unwarranted. Indications are, to the contrary, that crises freeze the restructuring process and that this is associated with the tight financial market conditions that follow*". This "reverse-liquidationist" view implies that, following a financial shock, productivity should grow less or even decay more for those industries that are more dependent on borrowed funds.

In a certain sense, both sides of the "liquidationist" approach share a common aspect with our model. They all predict that the effects of financial shocks on productivity depend on the reallocation of factors across firms and sectors. The central difference between these alternative frameworks is precisely how this reallocation takes place, which is the key for the ultimate impact of financial shocks on productivity. Our model predicts a non-monotonic relation between the impact of financial shocks on TFP and dependence on external finance. The liquidationist view suggests a positive relation, whereas the reverse liquidationist view points to a negative relation instead. Other models may also link changes in funding costs to TFP growth. However, differently from our model, and the "liquidationist" and "reverse-liquidationist" views, other approaches would generally rely on possible changes in firm-level TFP growth or the rate of technological improvement after financial shocks.[9]

III. EMPIRICAL STRATEGY

We start discussing the index of dependence on external finance constructed by RZ and utilized in our regressions. Then we describe the rest of the dataset and the steps followed to calculate sectoral TFP.

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[9] For instance, an increase in the cost of funds may affect the ability of firms to invest in new technologies that would increase productivity. If this is the case, we might observe a negative relationship between the cost of funds and productivity as industries become more reliant on external financing.

A. Dependence on External Finance

One central question in economics is whether financial development facilitates economic growth or the converse. Since theory is ambiguous with respect to the direction of causality, the question becomes, fundamentally, an empirical one. Studies trying to separate cause from consequence have been plagued by problems related to the lack of identification, since both economic growth and financial development tend to be highly endogenous in almost all regressions of one variable against measures of the other.

The seminal paper by Rajan and Zingales (1998) proposes a new method to identify empirically the effects of financial development on growth. The authors investigate whether industries that are more in need of external finance grow faster in countries possessing more developed capital markets. They find this is actually the case for a large set of economies over the 1980s. In order to implement their empirical procedure, RZ constructed an index of dependence on external finance for industries in the U.S. manufacturing sector. The authors assumed that this measure should be a valid index for the same industries in other countries as well. Their measure of dependence on external finance was calculated as the fraction of capital expenditures not financed with cash-flow from operations. The authors calculated the dependence on external finance for the median firm in each one of 36 industries in the U.S. manufacturing sector during the 1980s.

In defense of the validity of their empirical strategy, RZ assume that the index of dependence on external finance is relatively exogenous to other variables affecting financial development and economic growth. Their basic argument is that technology explains why some sectors depend more on external funds than others. In the authors' words: "*To the extent that the initial project scale, the gestation period, the cash harvest period, and the requirement for continuing investment differ substantially between industries, this is indeed plausible*".

Subsequent studies have utilized the RZ's index. Kroszner et al. (2007) investigate the impact of financial shocks on industry growth for 38 developed and developing countries. They find evidence that sectors that are more dependent on finance have lower growth rates of value added after financial crises. Dell'Aricia et al. (2008) conduct a similar study focusing on the real effects of banking crises. Braun and Larrain (2005) show that, in a sample of more than 100 countries, recessions have disproportionately negative effects on output growth for sectors that depend more on external funds.
Our paper differs from these studies in that it centers the analysis on the effects of financial shocks on TFP, not output. Moreover, we do not focus on crises periods, but instead analyze the response of TFP to regular movements in the cost of finance. This is a distinctive feature of the present study compared to Arizala et al. (2009), who use a similar technique to evaluate the impact of financial development on TFP growth in a panel of industries across

different countries. They also use RZ's measure, but their focus is on the low frequency movements in TFP[10] resulting from alternative degrees of financial development.

Focusing on TFP at the business-cycle frequency restricts our data significantly, since the type of information we need to construct robust measures of TFP at the industry level severely limits the sample both at the time series and cross-section dimensions. Notwithstanding, by analyzing the movements of an important component of output, it permits us a better comprehension of how financial shocks—even small ones—are transmitted to real activity.

A final word of caution regarding our use of the index of dependence on external finance is due. RZ calculated the index for industries classified according to the ISIC.[11] However, our data are constructed with information available for industries classified according to the NAICS.[12] For most industries, there is a very close match between both classification systems. Whenever necessary, we made some adjustments in order to make RZ's measure of dependence on external finance useful for industries classified according to the NAICS. The matching process is described in table 1 in appendix A. In what follows, the modified measure of dependence on external finance is denoted by MRZ. We conduct some robustness checks and present evidence that our results are not driven by potential distortions caused by the matching procedure.

B. Measuring Sectoral TFP Growth

In order to calculate sectoral TFP, we assume each sector's output is produced by a standard Cobb-Douglas technology that features constant returns to scale on capital and labor. In correspondence with the notation in the theoretical discussion, we have:

$$Y_s = A_s K_s^{\alpha_s} L_s^{1-\alpha_s}$$

where the exponents α_s are allowed to vary across sectors.

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[10] The authors explicitly average TFP growth for each industry over several years in order to eliminate fluctuations associated with the business cycle.

[11] International Standard Industrial Classification System.

[12] The North American Industry Classification System (NAICS) is utilized to measure activity at the industry-level in the United States, Canada, and Mexico. It has largely replaced the older Standard Classification Industrial (SIC) system. The NAICS is similar to the ISIC which was established by the United Nations. The first version of NAICS and the one used in the paper is from 1997.

We obtain data on output, capital and labor for 16 manufacturing industries in the United States and 15 industries in Canada between 1990 and 2007.[13] The data for U.S. industries were obtained as follows: Y_s is the Bureau of Economic Analysis's (BEA) series on value added by industry;[14] K_s is the series for capital services from the Bureau of Labor Statistics (BLS), multiplied by the index of capacity utilization provided by the Federal Reserve Board; L_s was obtained as the product of the series for actual average hours worked and the number of employees, both from the BLS. Similar Canadian data was extracted from STATSCAN's dataset. The exponent α_s for each U.S. industry was estimated as 1 minus the average fraction of value added paid as compensation to employees during the period 1997 to 2007. Data for the compensation of employees were obtained from the BEA. As for the Canadian manufacturing industries, the corresponding data were obtained from the Annual Survey of Manufactures and Logging, covering the period between 2004 and 2008. Table 2 summarizes the dataset.

Because sectoral TFP is calculated as a residual in the equation of production, it is important to carefully measure each component in that expression. This is the guiding principle behind our choice of variables. For instance, we use actual hours worked instead of number of employees since the first provides a better measure of the real flow of labor services used in the production process. This choice comes at the cost of severely restricting the time span in our data set, given that information on hours worked at the 3-digit NAICS level for the U.S. manufacturing industries is available since 1990 only. However, we believe it is a better choice compared to the alternatives; it minimizes the role of labor hoarding in response to shocks, allowing a more precise calculation of the true productivity of factors. Regarding the capital stock, we adjust it by capacity utilization in order to control for the possibility of capital hoarding in production. Our model in section II has no role for variations in capital utilization. In reality, the combination of uncertainty and adjustment costs in a dynamic setting might induce more volatility at the intensive margin (capital utilization) than at the extensive one (new investment), at least in the short run. Clearly, not controlling for the intensity of capital utilization creates bias in the measure of TFP. Table 2 shows that there is substantial volatility in the growth rate of capacity utilization in our sample, which reinforces the importance of using it to capture changes in the intensity of capital use.

[13] See the list of sectors in the appendix. There is no information regarding the capital stock for the transportation industry (NAICS code 336) in Canada, so we eliminate it from the sample.

[14] Chained 2000 dollars.

C. The Cost of Funds

Finally, we need a proxy for the cost of funds for corporations. Our baseline specification uses the yields on corporate bonds. For the United States, we use the yields on corporate bonds with maturity between 1 to 3 years collected by Bank of America Merryl Lynch. The corresponding data for Canada was obtained from the Canadian Central Bank. It is the series on the prime business loan rate, collected from chartered banks.[15]

Some readers might be concerned about the validity of employing the yields on corporate bonds as a measure of the cost of funds. Usually, only large corporations have full access to the bonds market, which means the yields might not be representative of the true cost of capital for smaller firms or individual entrepreneurs. Moreover, the series for the United States and Canada are based on interest rates applied for corporations in general, many of which are not in the manufacturing sector.

Considering these potential pitfalls, in section 5 we construct a measure of the cost of capital looking at expected returns on equity instead of debt. This construction is only valid for the United States, since the information on equity returns by manufacturing industry in Canada was not readily available. Hence, in section 5 we will compare the performance of our estimates for the United States only, using first the conventional yields on bonds and then our proxy for the cost of issuing equity.

IV. Estimation Results

This section shows estimates for the effect of changes in the cost of funds on TFP growth.

A. Baseline Regressions

Our initial specification for the regression equation is represented by:

$$\Delta\% TFP_{s,t} = d_t + d_s + \gamma_0 * MRZ_s * C_{s,t} + e_{s,t} \qquad (7)$$

where $\Delta\% TFP_{s,t}$ is the growth rate of TFP for sector s in year t, d_t and d_s are year and sector-specific dummies, MRZ_s is our index of dependence on external finance for sector s, $C_{s,t}$ represents the cost of funds for sector s in year t – the yield on corporate bonds- and $e_{s,t}$ is the residual. The focus is on the sign and magnitude of the estimated γ_0, which captures the differential impact of changes in the cost of finance on TFP growth.

[15] For robustness purposes, we have also used yields on corporate bonds of different maturities, as well as other relevant interest rates. Results are virtually unchanged.

Table 3 presents the results. The negative coefficient γ_0 is statistically significant at the 10 percent confidence level. Since the average sector in our sample has an MRZ index of approximately 0.28, the point estimate of γ_0 indicates that an increase of 100 basis points on the yields reduces the annual productivity growth of the average sector by nearly 0.25 percent relative to a sector that does not depend on external finance at all. Importantly, this magnitude is economically meaningful. To give a sense of proportion, the average annual growth rate of aggregate TFP for the U.S. economy between 1948 and 2000 is 1.18 percent, and it is around 0.53 percent from the 1970's until 2000.

We now test if the data support the non-monotonic relationship between the cost of finance and TFP growth across industries uncovered by the calibration of our model. As discussed before, our model predicts that the impact of increases in the cost of funds should be negative and more pronounced for industries with an index of dependence on external finance of approximately 0.5, whereas the effect should be nil for the extreme cases of no-dependence or full-dependence. We start checking this possibility by modifying the regression equation to:

$$\Delta\%TFP_{s,t} = d_t + d_s + \gamma_0 * MRZ_s * C_{s,t} + \gamma_1 * MRZ_s * C_{s,t} * Dhigh + e_{s,t} \qquad (8)$$

where $Dhigh$ is a dummy variable that assumes a value 1 for sectors with MRZ above 0.5 and a value 0 otherwise. Based on our model, we would expect γ_0 to be negative and γ_1 positive, and their sum to be approximately 0. Table 4 contains the results.

The estimates are remarkably in line with the theoretical predictions. A Wald test shows that the null hypothesis that

$$\gamma_0 + \gamma_1 = 0$$

cannot be rejected at conventional levels of significance. Hence, there is no evidence contrary to the prediction that polar sectors—in terms of their dependence on external finance—are equally affected by financial shocks. Interestingly, the point estimates in this case are much higher than in the original regression. For instance, an increase in the cost of funds by 100 basis points reduces the annual TFP growth of the average sector in our sample by more than 0.64 percent relative to a benchmark sector that does not depend on external funds.

The dummy approach utilized above is a simple but crude way of capturing the non-monotonicity predicted by the model, since it imposes a piecewise linear structure on the data. The qualitative results depicted in figure 1 suggest that the relation between financial shocks and TFP growth across the various industries can be better approximated by a quadratic equation. Hence, we estimate the following model:

$$\Delta\%TFP_{s,t} = d_t + d_s + \gamma_0 * MRZ_s * C_{s,t} + \gamma_1 * (MRZ_s)^2 * C_{s,t} + e_{s,t} \qquad (9)$$

The consistency of the estimates presented in Table 5 is striking. First, both γ_0 and γ_1 are significant at the 5 percent confidence level. More importantly, the two coefficients sum almost exactly to zero, which implies that the differential impact of financial shocks is nil not only for a benchmark sector with MRZ of 0, but also for a benchmark sector with MRZ of 1. Additionally, note that because γ_0 is negative and γ_1 is positive, the differential impact of financial shocks on TFP growth across sectors shall reach a minimum for a sector with MRZ given by:

$$MRZ = -\frac{\gamma_0}{2\gamma_1}$$

According to the point estimates in table 5, this ratio is virtually 0.5. This is exactly what the calibration results indicate. These estimates imply that an increase of 100 basis points in the cost of funds reduces the annual TFP growth of the average sector in our sample by roughly 0.63 percent relative to a benchmark sector that does not depend on external funds. Such sensitivity is virtually identical to the one uncovered by the piecewise linear approach presented above.

The central message emerging from these regressions is that financial shocks have a statistically significant and economically meaningful impact on TFP growth. However, as suggested by our stylized model, this effect is non-monotonic across the various manufacturing industries. Such an empirical non-monotonicity cannot be explained either by the liquidationist or by the reverse liquidationist approaches. In our view, it is quite surprising that our stylized framework can better account for the evidence compared to these well-established theories of the impact of recessions and financial crises on economic variables.

Importantly, our model has treated TFP at the firm level as an exogenous component, in line with work-horse macroeconomic models. To the extent that this assumption is valid, the empirical relation presented here is more than a pure co-movement between variables. We are inclined to conclude that the cost of funds is an important determinant of aggregate total factor productivity growth at the business cycle frequency due to reallocations of factors in the economy.

B. Robustness Checks

Sectoral TFP was calculated under the assumption that all sectors employ a Cobb-Douglas production function, which displays constant returns to scale in labor and capital. Hence, any test of the effects of the cost of funds on TFP is actually a joint test of the chosen specification for the production function, and the relation between financial shocks and productivity. The assumption of constant returns to scale is of particular interest for the discussion about productivity. If, in reality, technology displays non-constant returns to scale, variations in demand and the scale of operation will directly affect measured TFP. For instance, if the demand for the output of different sectors is also non-monotonically dependent on credit, increases in the cost of funds will reduce aggregate demand for the various industries in a non-monotonic fashion. This differential variation in demand combined with non-constant returns to scale might induce fluctuations in measured TFP. Under those circumstances, our regressions would be capturing the effect of financial shocks on demand

We formally address this possibility without substantially changing our baseline specification. Consider that the actual production technology of industry s is given by

$$Y_s = \tilde{A}_s{}^{*}\left(K_s{}^{\Psi_s} L_s{}^{1-\Psi_s}\right)^{\rho_s}$$

where $\tilde{A}_s{}^{*}$ is the industry's true TFP and ρ_s is a parameter that captures the degree of returns to scale for firms in sector s. Under those assumptions, our measure of TFP growth equals the growth in the unobserved technological component plus a bias that depends on the capital-labor ratio, the degree of returns to scale, and the scale of operation represented by the size of the labor force. More specifically, we have

$$\Delta\%TFP_{s,t} = \Delta\%\tilde{A}_{s,t}{}^{*} + (\Psi_s\rho_s - \alpha_s)\Delta\%\frac{K_{s,t}}{L_{s,t}} + (\rho_s - 1)\Delta\%L_{s,t}$$

Clearly, the bias in measured TFP growth depends both on the returns to scale and the size of operation of industries, which could be affected by movements in demand that result from changes in credit availability. In order to control for this possibility, we re-estimate the regressions of TFP growth including the growth in the capital-labor ratio and the growth in labor input as additional regressors: [16]

$$\Delta\%TFP_{s,t} = d_t + d_s + \gamma_0 MRZ_s C_{s,t} + \gamma_1 (MRZ_s)^2 C_{s,t} + b_0\Delta\%\frac{K_{s,t}}{L_{s,t}} + b_1\Delta\%L_{s,t} + e_{s,t} \qquad (10)$$

Table 6 shows that the u-shaped impact of the cost of funds on TFP growth is preserved, and its magnitude is slightly higher. Now, an increase of 100 basis points in the yields on corporate bonds reduces annual TFP growth in a sector with average dependence on external finance by 0.71 percentage point more than in a benchmark nondependent sector or fully-dependent sector. As a by-product of regression 4, the coefficient b_1 on labor growth gives us an idea about the nature of returns to scale. A positive estimate indicates increasing returns to

[16] Note that we allow the coefficients on these explanatory variables to vary across the various industries.

scale, while a negative number points towards decreasing returns. Unreported results indicate that most industries display fairly constant returns to scale.[17]

The inclusion of time dummies in the various regressions considered so far allows us to control for the effects of variables that, over time, have a common impact across the industries in our sample. For instance, this technique accounts for the effects of common shocks to TFP growth on the estimates. However, we cannot rule out the possibility that country-specific aggregate shocks are driving some of our results. We address this possibility as follows: i) separately for each country—the United States and Canada—we extract the first principal component from the series of TFP growth for the country's industries applying principal components analysis; ii) for each industry in a given country, we subtract the country's principal component from the TFP growth; and iii) we re-estimate the regressions using the "demeaned" data for productivity growth.

Table 7 displays the results for the baseline linear model, equation (7), as well as for the quadratic model, equation (8). First, we note that the extraction of this country-specific common component of TFP growth reduces the magnitude of the estimated coefficients capturing the impact of financial shocks. However, whereas the effect completely disappears for the simple linear case, the u-shaped relation predicted by our model is still preserved in the data. Despite the coefficient on the quadratic term being individually significant only at the 11 percent confidence level, a Wald test cannot reject the null hypothesis that the sum of coefficients in the non-linear model is zero. The new estimates for the non-monotonic model suggest that an increase of 100 basis points in bond yields reduces TFP growth for the average sector in our sample by approximately 0.48 percentage point more than for a nondependent sector. This is an economically meaningful effect. It is yet another piece of evidence supporting our simple model relative to the traditional liquidationist and reverse liquidationist approaches.

We also investigated to what extent our findings were driven by data from specific industries or by our adjustments to the original RZ index. Results show that this is not the case. First, we note that two sectors in our sample have a negative MRZ index. However, our model assumes that dependence on external finance is captured by a parameter that varies between 0 and 1. In order to accommodate this discrepancy, we replace the negative values of MRZ by zero, and re-estimate the baseline regression. The results are virtually unchanged. Second, as mentioned in section III, we made some adjustments in the measure of dependence on external finance in order to match the industry classification adopted by RZ and the one we use in the paper. To the extent that such modifications do not change

[17] Out of the 31 estimated coefficients on returns to scale, 24 are not significantly different from zero at the 5 percent confidence level. Basu (1996) also rejects the idea that increasing returns to scale could account for the procyclicality of productivity in the United States.

significantly the ranking of industries, they shall have no major effects on the estimation results. To check this claim, we reevaluate our regressions by sequentially excluding each one of the industries in both countries at the same time.[18] The basic conclusions remain valid in all cases.[19] Finally, TFP growth for the petroleum industry in the U.S. is much more volatile than for other industries, which could affect our results significantly (see Figure 2). Thus, we re-estimate the regressions excluding the observations for the U.S. petroleum industry[20] only and found that shocks to funding costs still have statistically significant effects on TFP growth.

V. CHANGES IN THE COST OF EQUITY AND TFP GROWTH

The market for corporate bonds is certainly not the only way businesses can raise funds. In practice, firms can rely on banks and equity issuance as well. The relative costs of funds in these different markets are jointly determined in equilibrium, giving some credence to the strategy of looking at one segment—corporate bonds—as representative of the broader scenario. However, it is important to consider the possibility that, at different points in time, firms substitute between debt and equity markets as their providers of marginal resources.

To verify the strength of our findings, we construct a proxy for the cost of equity instead of yields on corporate bonds and re-estimated the main regressions. In the entire section, we restrict the analysis to the United States only, since the required data on returns by industry portfolio was not readily available for Canada.

A. Measuring the Cost of Equity

In order to construct a measure of the cost of equity at the industry level, we assume that expected returns on stocks are generated according to the CAPM. The expected return for firm *i* in sector *s* is given by

$$E\left[R_{si}\right] = R^{f} + \beta_{si} E\left[R^{mkt} - R^{f}\right]$$

where R^{f} is the zero-beta rate of return, R^{mkt} is the return on the market portfolio and β_{si} is given by

$$\beta_{si} = \frac{Cov(R_{si}, R^{mkt})}{Var(R^{mkt})}$$

[18] With the exception of the transportation industry (NAICS code 336) which is present only for the U.S. data.

[19] Results available upon request.

[20] NAICS code 324.

Therefore, to calculate the expected return on equity for each firm, all we need is a measure of the expected return on the market portfolio and an estimate of β.

Let us start with the betas. Assume the realized returns on the stocks of individual firms can be decomposed in three parts:

$$\mathrm{R}_{si} = \mathrm{R} + \mathrm{R}_s + \mathrm{R}_i$$

where R is a common component across all stocks, R_s is a common component across all firms in sector s, and R_i is a pure idiosyncratic term, uncorrelated with returns of any other firms. Under those circumstances, we have

$$Cov(R_{si}, R^{mkt}) = Cov(R + R_s, R^{mkt}) + Cov(R_i, R^{mkt}) = Cov(R + R_s, R^{mkt})$$

Hence, betas are differentiated across industries[21] but are identical for all firms within a sector:

$$\beta_{si} = \beta_s$$

Industry betas are estimated using Fama and French returns on industry portfolios available at Professor Kenneth French's homepage.[22] More specifically, we run time series regression of the annual return on the portfolio of industry *s* securities on a constant and the annual return on the market portfolio.[23] To reduce the chance of important breaks over time in the covariance structure of returns, we discard the first 40 years of data, leaving us with observations of yearly returns between 1969 and 2008. The original dataset constructed by Fama and French presents returns on 49 industry portfolios. For most of the cases, there is a natural matching between their classification of industries and the one adopted in the paper. For a few cases, though, we had to average the original betas of two or three industries to obtain an adequate matching between the two classifications.[24]

We use the dividend yield on the market portfolio as a proxy for its expected returns. More precisely, we average the dividend yields of the 10th and 11th of 20 portfolios sorted on this measure. Our choice is based on a large volume of literature in asset pricing, greatly summarized in Campbell (2000) and Cochrane (2008). By construction—see Campbell and Shiller (1988)—a high dividend yield on any portfolio has to predict high future returns, high

[21] That is, to the extent that the industry component is not idiosyncratic too. As examples of industries in our sample, we have "Food, Beverage, and Tobacco" or "Chemical Products". At this level of aggregation, it is hard to claim the sectoral component would be completely idiosyncratic.

[22] http://www.mba.tuck.dartmouth.edu/pages/faculty/ken.french/

[23] See Kenneth French's homepage for details about the construction of each time series of returns.

[24] Details of this matching procedure are available upon request.

future dividend growth, or both. It turns out that, in the data, the dividend yield on the market portfolio in the United States is a good predictor of its future returns but has essentially no ability to predict future dividend growth. A high dividend yield today predicts high returns in the following years, while a low dividend yield predicts low returns.

In order to make this measure of expected returns useful for estimation purposes, it is normalized to have zero mean and standard deviation of 1. The normalized series is multiplied by each β_s, yielding a series that proxies the expected return on equity for each sector *s*. A central advantage of this proxy compared to the yields on corporate bonds is that it not only varies over time—because of variation in the dividend yield on the market portfolio—but it also varies across sectors—because each sector has a different exposure to the market portfolio.

B. Empirical Results

Since the dividend-yield predicts future equity returns, we interact industry betas with a one-period lag of the dividend yield on the market portfolio while constructing our measure of the cost of equity. We use this new measure for the cost of funds and re-estimate the three main specifications: the linear model, the dummy model, and the quadratic model.

Table 8 contains the estimation results using U.S. data only, both with the yields on corporate bonds and our proxy for expected returns on equity as measures of the cost of funds. First, we note that the coefficient estimates for using bond yields are virtually identical to the ones obtained with the full sample – including Canada. This suggests that there is nothing special about the U.S. in our sample. Second, the non-monotonicity of the impact of financial shocks on TFP growth across the various sectors is still preserved when using our measure of the cost of equity. However, the point estimates almost double in size relative to the estimates obtained from bond yields. Based on the results for the quadratic model, an increase of one standard deviation in the market dividend yield reduces TFP growth for the average sector in our sample by 1.29 percentage points more than in a benchmark nondependent sector – or a benchmark fully dependent sector.[25] Finally, the evidence for the linear model is weak since the coefficient on the interaction variable is not significant even at the 10 percent confidence level.

One potential explanation for the stronger estimated effects of the cost of equity compared to debt might be related to the cross-sectional variation of our measure of expected equity returns. As we mentioned earlier, the yields on corporate bonds we use in our previous estimations do not vary across industries, while our measure of the cost of equity does. This

[25] A Wald test cannot reject the null hypothesis that the sum of the coefficients in the quadratic model is zero.

lack of variability in the regressor might reduce the correlation between yields on bonds and sectoral TFP, diminishing the significance of the estimated coefficient.

Once more, returns to scale are hardly an explanation for the findings. Repeating the same steps performed before, we include the growth rate in the capital labor ratio and the growth rate in the labor force for each industry as explanatory variables. As it can be seen in table 9, the point estimates of the quadratic model become slightly higher in this case, and their statistical significance is reinforced. We also performed additional robustness tests similar to the ones discussed in the previous section – excluding individual sectors, zeroing the negative values for the MRZ, etc. The main findings are intact.

VI. Discussion

The evidence suggests that there is a strong negative, non-monotonic relationship between increases in the cost of funds and the TFP growth of different industries. This finding is particularly interesting given our effort to control for factor hoarding, a concern that drove our choice of using actual hours worked as a measure of labor and adjusting capital services by capacity utilization. Moreover, the sensitivity analysis has shown that returns to scale cannot explain our results.

We are skeptical about the importance of endogeneity problems. It is true that productivity, interest rates, and returns on equity are jointly determined in equilibrium. For instance, a positive productivity shock that is moderately persistent induces more investment and consumption—by the permanent income hypothesis logic—driving up the demand for funds and increasing equilibrium interest rates. This reverse causality, however, creates an upward bias in the estimated coefficients. It cannot, in itself, explain the non-monotonic – and always negative – impact that we find. Moreover, as discussed in the text, our results are robust to the control of common events – through the time dummies – and also country-specific aggregate shocks.

Of course, one can always argue that financial intermediaries anticipate industry-specific productivity shocks and adjust the cost of funds for each particular industry accordingly. As an example, consider a bank that observes a negative shock to the productivity of sector *s*. Fearing increases in delinquency rates, the natural response for the bank is to tighten credit conditions for firms in this sector. Such a mechanism induces a negative co-movement between the cost of funds and TFP growth, but the direction of causality is the contrary to the one we suggest in the paper. There is a central difficulty with this explanation though. First, this argument again has a hard time explaining the u-shaped pattern predicted by our model and found in the data. Second, the time-variation in our different measures of the cost of finance, the yields on corporate bonds and the dividend yield on the market portfolio, result from aggregate events. That is, we are not using sector specific borrowing costs.

Hence, for the reverse causality story to have a bite, one has to complement it with an explanation of why the common—average—cost of funds goes up precisely at the moment the sectors that have *intermediary* levels of dependence on finance have lower than average productivity relative to the sectors with very high or very low dependence. In other words, it is the *non-monotonic* correlation between the impact of the *aggregate* cost of funds on TFP growth and dependence on external finance that lends power to our findings. Endogeneity-based explanations have to take that into account.

The empirical results can be rationalized quite well by our stylized model, but they are at odds with the liquidationist and reverse-liquidationist views. In a certain sense, the three approaches share a common root. They all suggest that the link between financial shocks and aggregate TFP results from the reallocation of factors across firms with different degrees of efficiency. This is the crux of the matter. However, despite its simplicity, our framework is the only one that can reconcile this logic with the u-shaped pattern that we found in the data.

VII. Conclusion

This paper has shed light on the relation between financial shocks and TFP growth. In a nutshell, tighter credit conditions have a negative effect on factor productivity, contrary to the basic argument behind the "cleansing effect" theories. However, the magnitude of this effect varies non-monotonically with the degree of dependence on external finance. In our view, the negative link between credit conditions and TFP growth results from the poor allocation of factors across firms, reducing the productivity of entire industries.

Policymakers should pay attention to this lesson, especially in face of the events surrounding the recent financial crisis. The meltdown of the U.S. financial system and elsewhere caused sharp contractions of aggregate demand and increased unemployment. However, a full comprehension of the real consequences of the crisis also requires a close look at its effects on aggregate supply, with implications of utmost importance to macroeconomic management. For example, reductions in TFP diminish the magnitude of the output gap, with implications for monetary and fiscal policy.

Another important topic relates to the literature on economic depressions. The central finding behind these studies is that depressions are associated to sharp declines in aggregate TFP. Our paper suggests a possible mechanism explaining this fact. To the extent that economic depressions are initiated or followed by severe financial crises, the resulting misallocation of factors impairs efficiency, contributing to declines in production and income. An important open question is whether this efficiency effect is strong enough to justify the magnitude and persistence of the economic contraction.

Finally, our paper leaves many open questions for future research. From a microeconomic perspective, it would be interesting to analyze firm-level data in order to detect the potential misallocations resulting from financial shocks. If any, are the distortions caused simply by shifts in the scale of individual firms or is the composition of factors distorted as well?

APPENDIX A. TABLES

Table 1. Index of Dependence on External Finance

Matching with the RZ index

Industry	NAICS	Index MRZ	Corresponding Industry Rajan and Zingales	ISIC
Food, Beverage and Tobacco	311-312	-0.08	Average of Industries*	314,313,311
Apparel and Leather	315-316	-0.06	Average of Industries*	323,322
Primary Metal	331	0.05	Average of Industries*	371,372
Mineral	327	0.06	Nonmetal	369
Paper	322	0.18	Paper	341
Printing	323	0.2	Printing and Publishing	324
Chemical	325	0.21	Average of Industries*	35,113,513,352
Fabricated Metal Products	332	0.24	Metal	381
Furniture	337	0.24	Furniture	332
Wood	321	0.28	Wood	331
Petroleum	324	0.33	Petroleum and Coal	354
Transportation	336	0.39	Motor Vehicle	3843
Textile	313-314	0.4	Textile	321
Machinery	333	0.45	Machinery	382
Plastic	326	0.69	Average of Industries*	356,355
Electrical Appl. And Comp.	335	0.96	Average of Industries*	38,253,833,832

* Arithmetic average of RZ's index of dependence on external finance for the industries in the ISIC column.

Table 2. Descriptive Statistics

(Annual percent change, except yields which are in levels.)

Variable	Mean	Std. Dev.	Min	Max	Obs
TFP	1.53	5.96	-29.32	30.50	527
Labor	-1.11	4.93	-16.72	23.38	527
Capacity Utilization	-0.03	4.26	-19.28	14.48	527
GDP	1.12	7.41	-27.68	30.74	527
Capital-Labor Ratio	1.82	5.02	-22.04	18.24	527
Yields	5.73	1.40	2.52	8.26	527

Include data for U.S. and Canadian industries.

Table 3. Baseline Regression

Dependent Variable: Percent change in TFP

Variable	Estimate	Std. Dev.
MRZ×Cost of Debt	-0.87*	0.48
Year Dummies	Yes	
Sector Dummies	Yes	
Observations	527	

*Significant at the 10 percent confidence level.

Include data for U.S. and Canadian industries.

Table 4. External Finance Dependence Regression

Dependent Variable: Percent change in TFP

Variable	Estimate	Std. Dev.
MRZ×Cost of Debt	-2.29***	0.77
MRZ×Cost of Debt×Dhigh	1.80**	0.82
Year Dummies	Yes	
Sector Dummies	Yes	
Wald chi2(49)	296.46	
Observations	527	

***Significant at the 1 percent confidence level.

**Significant at the 5 percent confidence level.

Include data for U.S. and Canadian industries.

Table 5. Quadratic Regression

Dependent Variable: Percent change in TFP

Variable	Estimate	Std. Dev.
MRZ×Cost of Debt	-3.08***	1.14
MRZ^2×Cost of Debt	2.98**	1.49
Year Dummies	Yes	
Sector Dummies	Yes	
Wald chi2(49)	295.55	
Observations	527	

***Significant at the 1 percent confidence level.
**Significant at the 5 percent confidence level.
Include data for U.S. and Canadian industries.

Table 6. Quadratic Regression with Returns to Scale and Industry Size

Dependent Variable: Percent change in TFP

Variable	Estimate	Std. Dev.
MRZ×Cost of Debt	-3.65***	1.06
MRZ^2×Cost of Debt	3.90***	1.49
Year Dummies	Yes	
Sector Dummies	Yes	
Capital-labor Ratio	Yes	
Growth in Labor Input	Yes	
Wald chi2(111)	642.35	
Observations	527	

***Significant at the 1 percent confidence level.
Include data for U.S. and Canadian industries.

Table 7. Country-specific Principal Component Regression

Dependent Variable: Percent change in TFP, Restricted

Variable	Estimate	Std. Dev.
Linear Model		
MRZ×Cost of Debt	-0.52	0.48
Quadratic Model		
MRZ×Cost of Debt	-2.36**	1.14
MRZ^2×Cost of Debt	2.37	1.48
Observations	527	

**Significant at the 5 percent confidence level.

Include data for U.S. and Canadian industries.

Table 8. Cost of Equity vs. Cost of Debt

Dependent Variable: Percent change in TFP

Equity			*Debt*		
Variable	**Estimate**	**Std. Dev.**	**Variable**	**Estimate**	**Std. Dev.**
Linear Model					
MRZ×Cost of Equity	-1.50*	0.94	MRZ×Cost of Debt	-0.84	0.73
Piece-wise Linear Model					
MRZ×Cost of Equity	-6.08***	1.72	MRZ×Cost of Debt	-3.39***	1.23
MRZ×Cost of Equity×Dhigh	4.91***	1.58	MRZ×Cost of Debt×Dhigh	2.88***	1.16
Quadratic Model					
MRZ×Cost of Equity	-6.01**	2.73	MRZ×Cost of Debt	-3.81**	1.76
MRZ^2×Cost of Equity	5.00**	2.91	MRZ^2×Cost of Debt	3.59*	2.02
Observations	272				

***Significant at the 1 percent confidence level.
**Significant at the 5 percent confidence level.
*Significant at the 10 percent confidence level.

Include only data for U.S. industries.

Table 9.

Dependent Variable: Percent change in TFP

Variable	Estimate	Std. Dev.
MRZ×Cost of Equity***	-7.00***	2.54
MRZ^2×Cost of Equity***	6.39***	2.69
Wald chi2(66)	253.02	
Observations	272	

***Significant at the 1 percent confidence level.

Includes only data for U.S. industries.

APPENDIX B. FIGURES

Figure 1.

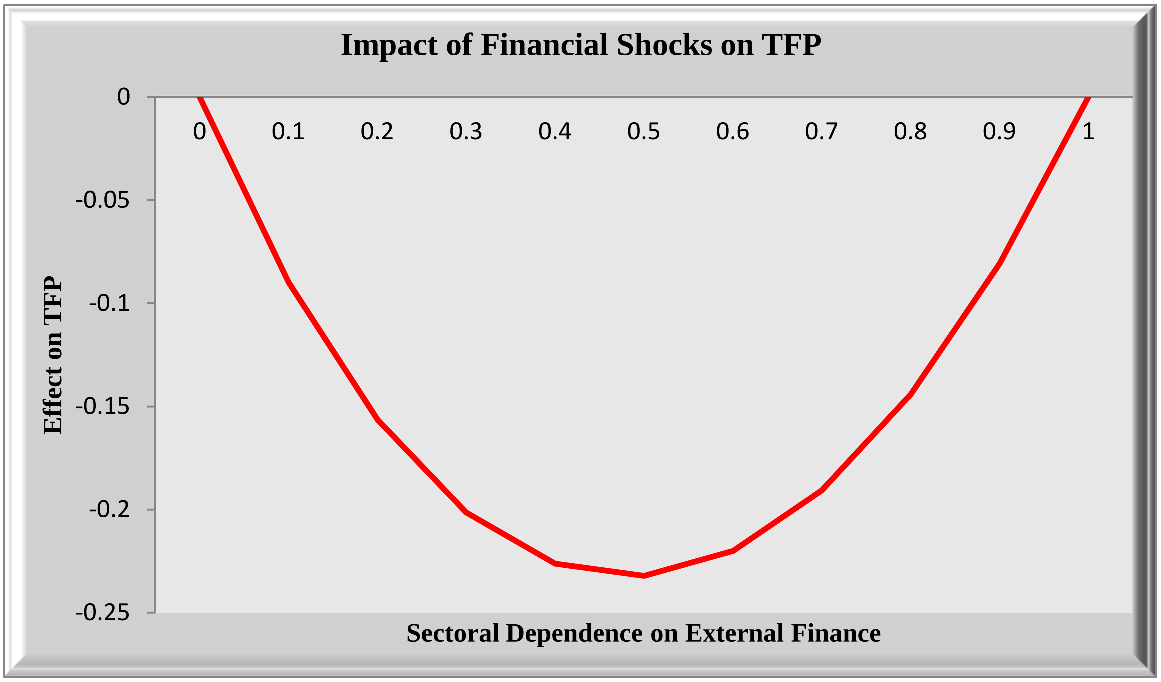
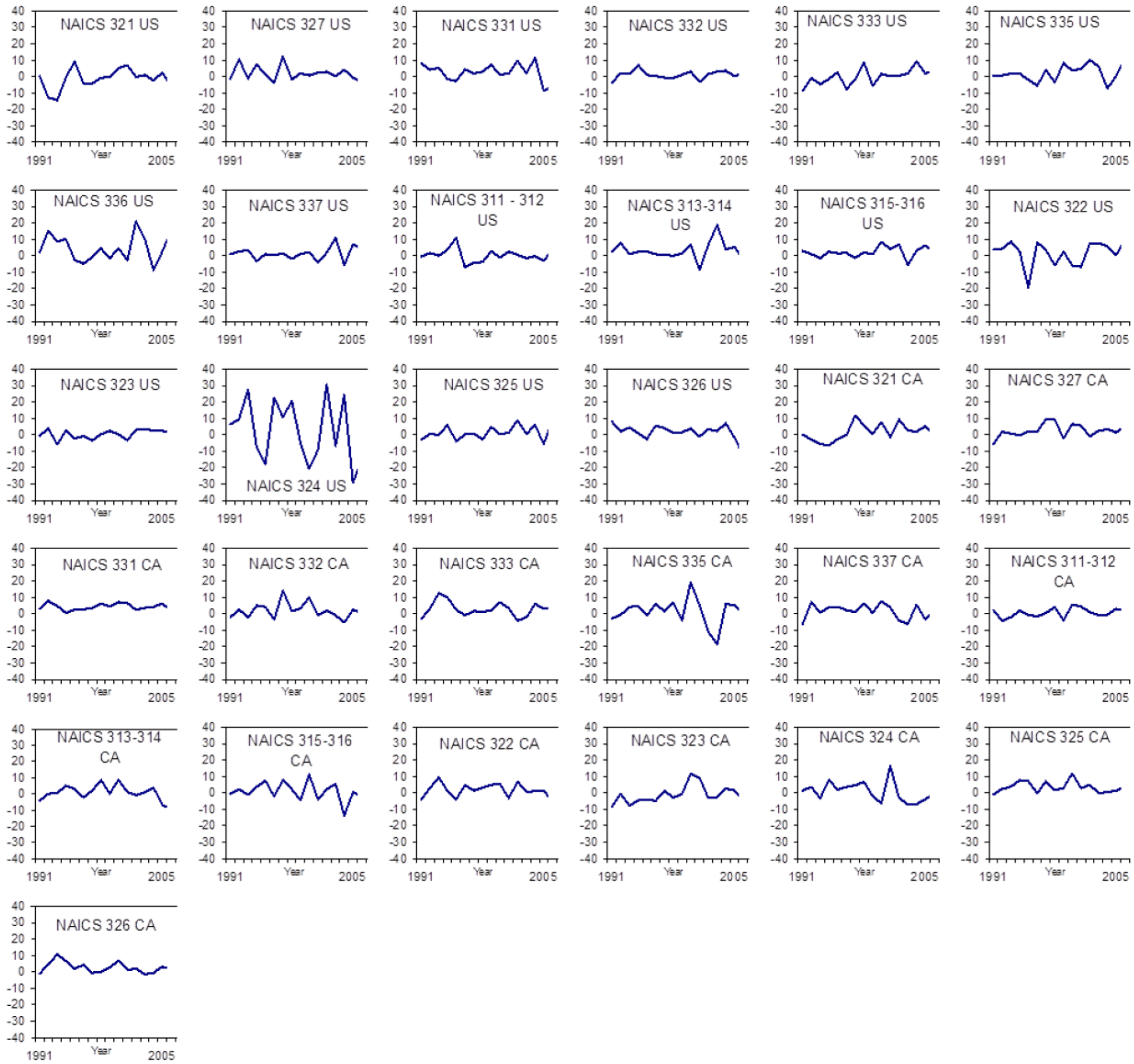


Figure 2.

(percent change in TFP, LH axis)



APPENDIX C. PROOFS OF PROPOSITIONS

PROOF OF PROPOSITION 1:

For any firms *i* and *j* in industry s, their relative labor forces are given by:

$$l_{sj} = \left(\frac{\tilde{A}_{sj}}{\tilde{A}_{si}}\right)^{\sigma-1} \left\{\frac{\left[\frac{(1-\theta_s)+\theta_s\beta_{si}\tau}{(1-\theta_s)q_{si}+\theta_s}\right]}{\left[\frac{(1-\theta_s)+\theta_s\beta_{sj}\tau}{(1-\theta_s)q_{sj}+\theta_s}\right]}\right\}^{\sigma} l_{si}$$

Summing both sides of the equation in *j* and rearranging terms, we obtain

$$l_{si} = \left\{\left\{\frac{\left(\tilde{A}_{si}\right)^{\sigma-1}}{\left[\frac{(1-\theta_s)+\theta_s\beta_{si}\tau}{(1-\theta_s)q_{si}+\theta_s}\right]^{\sigma}}\right\} \Big/ \sum_{j=1}^{N}\left\{\frac{\left(\tilde{A}_{sj}\right)^{\sigma-1}}{\left[\frac{(1-\theta_s)+\theta_s\beta_{sj}\tau}{(1-\theta_s)q_{sj}+\theta_s}\right]^{\sigma}}\right\}\right\} L_s$$

where $L_s = \sum_{j=1}^{N} l_{sj}$ is the total labor employed in sector s. Hence, we have

$$l_{si} = \gamma_{si} L_s$$

Since the capital-labor ratio is identical for all firms in that industry, we have

$$\frac{k_{si}}{l_{si}} = \frac{\alpha_s}{1-\alpha_s}\frac{w}{r} = \frac{K_s}{L_s}$$

Sectoral output can be written as

$$Y_s = \left[\sum_{i=1}^{N} y_{si}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} = \left[\sum_{i\in\Omega_s}\left(\tilde{A}_{si}k_{si}{}^{\alpha_s}l_{si}{}^{1-\alpha_s}\right)^{\frac{\sigma-1}{\sigma}} + \sum_{i\notin\Omega_s}\left(0k_{si}{}^{\alpha_s}l_{si}{}^{1-\alpha_s}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

Using the optimality conditions, we have

$$Y_s = \left[\sum_{i\in\Omega_s}\left(\tilde{A}_{si}\left(\frac{K_s}{L_s}\right)^{\alpha_s}\gamma_{si}L_s\right)^{\frac{\sigma-1}{\sigma}} + \sum_{i\notin\Omega_s}\left(0\left(\frac{K_s}{L_s}\right)^{\alpha_s}\gamma_{si}L_s\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

or

$$Y_s = \left[\sum_{i\in\Omega_s}\left(\tilde{A}_{si}\gamma_{si}\right)^{\frac{\sigma-1}{\sigma}} + \sum_{i\notin\Omega_s}\left(0\gamma_{si}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} K_s^{\alpha_s} L_s^{1-\alpha_s}$$

which implies that

$$A_s = \left[\sum_{i\in\Omega_s}\left(\tilde{A}_{si}\gamma_{si}\right)^{\frac{\sigma-1}{\sigma}} + \sum_{i\notin\Omega_s}\left(0\gamma_{si}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} = \left[\sum_{i\in\Omega_s}\left(\tilde{A}_{si}\gamma_{si}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

Q.E.D.

PROOF OF PROPOSITION 2:

If $q_{si} = q_s$ for every firm i in sector s, the expression for γ_{si} boils down to

$$\gamma_{si} = \left\{\frac{\left(\tilde{A}_{si}\right)^{\sigma-1}}{\left[\frac{(1-\theta_s)+\theta_s\beta_s\tau}{(1-\theta_s)q_s+\theta_s}\right]^{\sigma}}\right\} \Bigg/ \sum_{j=1}^{N}\left\{\frac{\left(\tilde{A}_{sj}\right)^{\sigma-1}}{\left[\frac{(1-\theta_s)+\theta_s\beta_s\tau}{(1-\theta_s)q_s+\theta_s}\right]^{\sigma}}\right\} = \gamma_s$$

since β_s becomes identical to every firm as well. This allows us to rewrite the relative sizes as

$$\gamma_s = \left(\tilde{A}_{si}\right)^{\sigma-1} \Big/ \sum_{j=1}^{N}\left(\tilde{A}_{sj}\right)^{\sigma-1}$$

Which is independent of τ. Therefore, aggregate productivity becomes invariant to changes in the overall cost of funds. The same logic applies if $\theta_s = 1$ or $\theta_s = 0$.

Q.E.D.

APPENDIX D. CALIBRATION

We simulate an economy with 11 different industries, each composed by 100 firms - the uniform distribution of firms across industries is absolutely irrelevant for the analysis. Industries are ordered according to their dependence on external finance θ_s. We assume θ_s has a discrete uniform distribution in the interval [0, 1] , with a different value for each of the 11 industries. Hence, the first industry does not depend on external finance at all - $\theta_1 = 0$ - whereas the last industry is fully dependent on it - $\theta_{10} = 1$. The parameter determining the elasticity of substitution across goods within an industry σ is set equal to 4. Naturally, the qualitative results are invariant for different choices of σ.

In each sector, the TFP across the various firms is uniformly distributed in the interval [0.5, 1.5] – note that the change in firm-level productivity is totally exogenous. The common interest rate on external funds assumes two possible values. In the absence of financial shocks, it is calibrated to 3 percent a year. If a financial shock hits, the rate goes up to 10 percent a year. The cost of external funds faced by each firm is the product of this common rate and the inverse of the probability of survival q_{si}. In the baseline calibration that originated figure 1 in the text, we assume the q_{si} is uniformly distributed in the interval [0.5, 1]. We initially assume that q_{si} is perfectly negatively correlated with g_i . That is, for each sector s, firm 1 survives for sure but has the lowest TFP, whereas firm 100 has only a 50 percent chance of survival but has the highest TFP conditional on not dying.

This perfect negative relation between probability of survival and TFP is, of course, an extreme assumption. In order to test for the robustness of the qualitative results illustrated in figure 1, we considered weaker degrees of cross-sectional dependence between the two variables. We perturbed the original probabilities with independent noise and re-computed the impact of financial shocks on productivity growth. For example, we shrink the original probabilities to lie uniformly in the interval [0.5 + a, 1 - a], where $a \in (0, 0.25)$; then we add, to each probability, a random variable drawn from the uniform distribution in the interval [-a, a]. For each choice of a we repeat this process 10,000 times and compute the average effect of the increase in the cost of funds on TFP across sectors. This strategy moves the correlation between probability of survival and TFP growth much closer to zero – the more so the larger a. Yet, the non-monotonic and negative effect on productivity is still preserved.

As for the case of productivity growth, the basic structure of the calibration was maintained. We considered two periods and assumed that all firms start with the same level of productivity. Now, however, it is productivity *growth* across the various firms in each sector that is distributed uniformly distributed in the interval [0.5, 1.5].We then compute the TFP growth observed under low interest rates versus the TFP growth observed under high interest rates.

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