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Financial Shocks and TFP Growth

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Financial Shocks and TFP Growth

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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 finding 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. Based on a stylized theoretical model, the estimates suggest that financial shocks distort the allocation of factors across firms even within an industry, reducing its TFP. The decline in productivity growth accounts for a large fraction of the negative impact of funding costs on output.

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I. INTRODUCTION

How do financial shocks propagate through the real economy? Economists have devoted great effort to answer this question. Traditional neoclassical business cycle theories imply a straightforward connection between financial shocks and economic activity. According to these theories, increases in funding costs should depress investment and consumption, reducing aggregate demand. Moreover, the negative effects on investment reduce capital accumulation, impairing the economy's ability to produce output in the future. Hence, both supply and demand should contract after financial shocks. Nonetheless, the majority of theoretical and empirical specifications posit that efficiency, in particular total factor productivity (TFP), should be exogenous to financial conditions.

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 aggregate TFP 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 aggregate TFP and financial shocks is hard to establish. To setup an easily testable link between financial shocks and total factor productivity, we develop a stylized model in the spirit of Chari et al. (2007) in which

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

sectoral dependence on external finance appears as a useful identifying device. According to the model, if distortions introduced by financial frictions are homogenous across firms within an industry, then sectoral TFP should not be affected by financial shocks that move the overall cost of funds. However, if credit frictions vary substantially across firms when funding costs change, sectoral TFP would be affected as firms' scale deviate from their optimal size in the absence of such frictions. The effect would be larger in sectors that are more dependent on external financing. Specifically, our model suggests that if increases in corporate bond yields or in the cost of issuing equity are followed by greater cross-firm dispersion in financial friction, sectoral TFP growth would decline.

With the model in mind, the paper sets up a test for the effect of financial shocks on TFP growth and shows that, indeed, changes in the cost of funds impact the economy above and beyond what would be expected from standard theories of fluctuations. 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 reduce not only the scale of operation of different sectors, but also 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 output and its components: capital, labor and TFP. We find that sectors that are more dependent on external finance face sharper contractions of output, capital and labor in face of higher cost of funds. Interestingly, we also show that TFP declines more in those sectors too. 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 such a decline.

Our methodology is based on interacting 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 productivity in general. 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 the 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 our 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 0.25 percentage point below TFP growth in a benchmark sector that would not depend on external sources of funding. This is almost half of the average growth rate of aggregate TFP for the U.S. economy in the last 20 years.

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. Basically, 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 0.5 percentage point vis-à-vis a benchmark sector that would not depend on external sources of funding.

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 for each manufacturing industry.

The remainder of the paper is organized as follows. Section 2 presents a stylized neoclassical model and discusses alternative theories relating TFP to the cost of funds. It can be skipped by those readers more interested in the empirical results. 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 some 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. Section 6 concludes. The appendix contains all figures and tables as well as a description of calibration exercises.

II. THEORY

A. 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. Industry output Y_s is the result of a CES aggregator of firm specific output Y_{si} as follows:

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

Firms are created by entrepreneurs who live for one period and start life without any endowment. Each individual firm has some monopoly power in the market for its product, since goods are not perfectly substitutes even within a sector. In order to produce, firm *i* in industry *s* hires labor accumulates capital and combines both inputs using a Cobb-Douglas technology

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}$$

where A_{si} is a measure of firm *i*'s total factor productivity. Both labor (L_{si}) and capital (K_{si}) are hired in competitive markets for factor inputs at the prices *w* and *R* respectively. Factor prices are the same for every firm since inputs are freely mobile across sectors.

We assume that, at every period, a fraction ϕ of the costs of production have to be paid up front, at the very same moment factors are hired. 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

[3] See Newmeyer and Perri (2004) for example.

stages of the production process. We assume that ϕ 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, which could be due to unmodeled technological or market structure heterogeneity. Such an assumption is in line with the claims in RZ's construction of their index of dependence on external finance.

Because entrepreneurs do not have any resources while starting their businesses, they have to rely on financial markets to raise the funds necessary to pay the upfront costs. Due to unmodeled asymmetric information and sources of frictions, the cost of funds for borrowers, denoted by τ , may vary across sectors and firms. More specifically, the cost of working-capital has three distinct components:

$$\tau_{si} = \overline{\tau} + \tau_s + \tau_i$$

The first term represents a common funding cost for the whole economy, the second term is specific to firms in sector s. Finally, the last term is an idiosyncratic element, whose cross-sectional mean is zero since it is already incorporated in τ_s . The cost τ_{si} can result from the activity of financial intermediation characterized by segmented markets, incomplete contracts and asymmetric information. For instance, we can suppose that lenders observe a noisy signal about productivity A_{si} , and cannot write contracts contingent on the ex-post realization of production. If entrepreneurs are allowed to default on their debts, we have all the ingredients necessary for the cost of funds to vary across firms.

Given this set up, the problem of an individual entrepreneur in sector s can be written as:

$$max_{P_{si},L_{si},K_{si}} \left\{ P_{si}Y_{si} - (1-\phi_s)\left[wL_{si} + RK_{si}\right] - \phi_s (1+\tau_{si})\left[wL_{si} + RK_{si}\right]\right\}$$
$$\text{s.t.} \quad P_{si} = P_s \left(\frac{Y_s}{Y_{si}}\right)^{\frac{1}{\sigma}}$$

where P_s and Y_s denote the sectoral price level and output respectively, and P_{si} is the price chosen by firm *i*. The expression for P_s is given by

$$P_s = \left(\sum_{i=1}^{N} P_{si}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$$

As usual, the solution to this maximization problem is obtained assuming the individual firm takes the sectoral variables as given. In any optimal allocation, we have:

$$\frac{K_{si}}{L_{si}} = \frac{\alpha_s}{1-\alpha_s}\frac{w}{R} = \frac{K_s}{L_s} \tag{1}$$

$$L_{si} = \left(\frac{A_{si}}{A_{sj}}\right)^{\sigma-1}\left(\frac{1+\phi_s\tau_{sj}}{1+\phi_s\tau_{si}}\right)^{\sigma} L_{sj} \tag{2}$$

where L_s and K_s are the aggregate stocks of labor and capital utilized in industry *s*.

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 A_s is a measure of total factor productivity for industry *s*. This comes at no cost in terms of generality, since we have not imposed any restriction about the nature of A_s. Proposition 1 below shows how A_s depends only on the true technological elements A_{si} and the cost of capital. Let us establish some useful notation first.

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

$$\gamma_{si} = \left(\frac{A_{si}^{\sigma-1}}{\left(1+\phi_s\tau_{si}\right)^{\sigma}}\right) / \sum_{i=1}^{N}\left(\frac{A_{si}^{\sigma-1}}{\left(1+\phi_s\tau_{si}\right)^{\sigma}}\right)$$

Proposition 1. *The expression for total factor productivity in industry s is given by*

$$A_s = \left(\sum_{i=1}^{N}\left(\gamma_{si}A_{si}\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

Proof. From the optimality condition represented by equation 2 we obtain:

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

Substituting this expression in the production function for firm *i* and recognizing, from equation 1, that the capital-labor ratio for the individual firm is identical to the capital-labor ratio for the sector as a whole, we get:

$$Y_{si} = \gamma_{si} A_{si} \left(\frac{K_s}{L_s} \right)^{\alpha_s} L_s$$

Raising both sides to the power $\frac{\sigma-1}{\sigma}$, summing over i and raising again both sides now to the power $\frac{\sigma}{\sigma-1}$, we arrive at

$$Y_s = \left[\left(\sum_{i=1}^{N} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \right] = \left(\sum_{i=1}^{N} \left(\gamma_{si} A_{si} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \left(\frac{K_s}{L_s} \right)^{\alpha_s} L_s$$

Sectoral TFP resembles a weighted average of firm specific TFP, where the weights, represented by γ_{si}, sum to 1 and depend on the cost of external funds for the individual firms. An immediate consequence of proposition 1 is that, if the cost of external funds is identical across firms within an industry, its TFP will result exclusively from technological elements. Indeed, an identical τ for all firms in industry *s* turns the expression for γ_{si} into

$$\gamma_{si} = \frac{A_{si}^{\sigma-1}}{\sum_{i=1}^{N} A_{si}^{\sigma-1}}$$

We formalize this result as a corollary of proposition 1.

Corollary. If $\tau_i = 0$ for all firm *i* in industry *s*, the industry TFP is given by

$$A_s = \left(\sum_{i=1}^{N} A_{si}^{\sigma-1} \right)^{\frac{1}{\sigma-1}}$$

This corollary yields the testable prediction that, if financial distortions are not firm specific, sectoral TFP should not be affected by financial shocks, no matter the degree of dependence of firms on external funding. It is interesting to note that this is the total factor productivity that would be achieved by a social planner trying to maximize total output while restricted to choose the optimal allocation of production across firms in industry *s* subject to the total endowments of K_s and L_s.

Pinning down the connection between sectoral TFP and financial shocks is much harder when heterogeneity in the cost of funding is taken into account. Proposition 1 shows that TFP at the industry level depends on the weighted sum of firm level TFP, which is assumed exogenous. Hence, financial shocks affect sectoral productivity only through a reshuffling of the weights γ_{si}. The direction of this reshuffling and the ultimate effect on sectoral TFP depends on the nature of financial frictions.

The weights are determined by the relative scale of individual plants. Because all plants in an industry use the same capital-labor ratio, the scale of each plant can be characterized exclusively by the size of its labor force, given by:

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

Hence, the scale of firm i relative to its peer j in industry s is expressed as

$$\frac{L_{si}}{L_{sj}} = \frac{\gamma_{si}}{\gamma_{sj}} = \left(\frac{A_{si}}{A_{sj}}\right)^{\sigma-1} \left(\frac{1+\phi_s \tau_{sj}}{1+\phi_s \tau_{si}}\right)^{\sigma}$$

The relative magnitudes of plants depend on their relative productivities and the relative distortions introduced by the cost of external finance. When these distortions are absent or when they are homogenous across firms,[4] the relative scales will be driven exclusively by the ratio of technological components. As mentioned before, this ratio is the only information a planner would take into account while distributing a given amount of inputs in order to maximize sectoral output. Intuitively, the more productive firms should be larger than their less productive counterparts. Heterogeneity in the cost of external funds breaks this tight link between scale and productivity, moving the industry inside its production possibilities frontier, yet each individual firm is making optimal choices. Basically, the dispersion of financial frictions distorts the allocation of factors across firms.

To fix ideas, consider the case of a sector *s* with only 2 firms. A social planner faced with total inputs K_s and L_s would equalize capital-labor ratios across firms. If her objective is to maximize total output in the industry, she will distribute labor (and capital) across firms in order to maximize sectoral TFP. In other words, the planner would choose the weight γ_{s1} to solve the following problem:

[4] For instance, this will be the case when lenders are risk neutral, firm-specific risks can be diversified, and firms cannot send credible signals about the likelihood of their solvency.

$$max_{\gamma_{s1}}\left[\left(\gamma_{s1}A_{s1}\right)^{\frac{\sigma-1}{\sigma}}+\left(\left(1-\gamma_{s1}\right)A_{s2}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

Because the objective function is concave in γ, the unique solution features

$$\frac{\gamma_{s1}^{*}}{1-\gamma_{s1}^{*}}=\left(\frac{A_{si}}{A_{sj}}\right)^{\sigma-1}$$

The farther away the market allocation is from this optimal, the smaller sectoral TFP. The heterogeneity in the cost of funds across firms introduces a wedge in the optimal allocation, which is represented by

$$wedge_{s}^{1,2}=\left|1-\left(\frac{1+\phi_{s}\tau_{s2}}{1+\phi_{s}\tau_{s1}}\right)^{\sigma}\right|$$

Therefore, the impact of financial shocks on TFP hinges upon the response of the financial wedge to these shocks.

Consider first the case of a shock that raises the common component of the cost of funds $\overline{\tau}$. It is easy to see that this moves the ratio of financial distortions closer to 1, pushing the financial wedge towards zero and boosting sectoral TFP. Moreover, other things equal, the gain in TFP is increasing in the dependence on external finance ϕ. Because sectors with high ϕ have initial allocations that are more distant from the optimal, a given reduction in the financial wedge will be more potent in increasing TFP. Additionally, a high ϕ implies a larger reduction in the financial wedge for any given change in $\overline{\tau}$.

A second possibility is that financial shocks manifest through changes in the distribution of the idiosyncratic component τ_i. For example, during financial duress, lenders might improve their screening devices to better evaluate the creditworthiness of borrowers, increasing the heterogeneity in τ_i. In our example with two firms in industry *s*, this increase in heterogeneity feeds the wedge, decreasing sectoral TFP, the more so the higher is ϕ.[5] The converse holds in case heterogeneity in τ_i declines following shocks, for example because sentiment deteriorates and lenders become reluctant to lend to borrowers in general.

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[5] The logic behind this conclusion is exactly the same as the one outlined for the case where $\overline{\tau}$ increases. One just needs to reverse the argument.

The central lesson from the two-firm example is that changes in the cost of funding will increase sectoral TFP to the extent that they level the playing field of access to finance for different firms. These effects are more potent for those sectors that depend more on external resources. Heterogeneity in the cost of funds distorts the optimal allocation of factors within each industry, since the relative scales of plants respond to additional information beyond that contained in relative TFPs. Interestingly, this result is robust to any specification of the joint distribution of productivity and the idiosyncratic component of the cost of funds. It does not depend on whether more productive firms can borrow at lower or higher rates compared to their less productive competitors.

We can extend this logic to analyze the case where the number N of firms in industry s is large. Although the algebra is more cumbersome, the economic intuition is identical to the previous example. For any two firms i and j in industry s, the financial wedge is represented by the same expression as before:

$$wedge_s^{i,j} = \left| 1 - \left(\frac{1+\phi_s \tau_{sj}}{1+\phi_s \tau_{si}} \right)^{\sigma} \right|$$

An increase in the common component of funds reduces the wedges for all pairs of firms i and j, moving the sector closer to its efficiency frontier and boosting its TFP. Furthermore, the gain in TFP is still increasing in ϕ. On the other hand, financial shocks that raise the dispersion of the idiosyncratic component τ_i have negative effects on TFP, the more so the higher the dependence on external finance.

For illustrative purposes, we calibrate the model and analyze the response of TFP after a financial shock.[6] Figures 1 and 2 display the percentage change in sectoral TFP in response to two alternative shocks as a function of the dependence on finance, ϕ. Figure 1 considers the case where $\overline{\tau}$ jumps for a given dispersion in τ_i, while figure 2 depicts the case where the dispersion of τ_i increases for a given $\overline{\tau}$. While constructing both figures, we have considered three possibilities with respect to the correlation between the idiosyncratic cost of finance τ_i and firm-level productivity A_{si}: perfect positive correlation, perfect negative correlation, and zero correlation. Because all cases yield virtually identical results, only the zero correlation scenario is presented. As one can see, the graphs confirm our predictions.

[6] The details of the calibration exercise are described in the appendix.

So far we have considered only two types of financial shocks: increases in $\overline{\tau}$ or increases in the dispersion of τ_i. As seen above, these two possibilities have completely opposite effects. This separation has been done for pedagogical purposes only. It is likely that actual financial shocks contain characteristics of both cases. Nonetheless, with the exception of the very unlikely event that both effects exactly offset each other, financial shocks shall have a differential impact on TFP according to the dependence of an industry on borrowed funds. It is precisely this differential impact that is so important to us, because it permits a cleaner identification from an econometric point of view of the true effects of changes in financial markets on TFP.

Finally, it is important to emphasize that the analysis has focused exclusively on TFP and its relation 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 affect aggregate demand, which has implications for these very same variables. Productivity, on the other hand, should be relatively immune to such variations, at least from the perspective of a standard neoclassical model. Moreover, the model is extremely simple and is not meant to fully capture the nature of the relation between the cost of finance and TFP or 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,[7] 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 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 the death rate of outdated plants should be higher.

Economists have not reached an agreement with respect to the validity of the "cleansing-effect" story, especially during recessions. Recessions and crises can impose frictions in the

[7] See De Long (1990).

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 key for the ultimate impact of financial shocks on productivity. Other mechanisms may also link changes in funding costs to TFP growth. However, differently from our model, and the "liquidationist" and "reverse-liquidationist" views, which focus on how financial shocks affect market efficiency, other mechanisms would generally rely on possible changes in firm-level TFP growth or the rate of technological improvement after financial shocks.[8]

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.

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.

[8] 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.

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[9] resulting from alternative degrees of financial development.

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

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.[10] However, our data are constructed with information available for industries classified according to the NAICS.[11] 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.

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.[12] The data for U.S. industries

[10] International Standard Industrial Classification System.

[11] 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.

[12] 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.

were obtained as follows: Y_s is the Bureau of Economic Analysis's (BEA) series on value added by industry;[13] 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 industry was estimated using U.S. data. They were calculated 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 was obtained from the BEA. We assume that Canadian manufacturing industries employ similar production technologies, which means they share common production coefficients α_s. 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, since there is no uncertainty at the time entrepreneurs hire inputs and adjustment costs are absent. In reality, the combination of uncertainty and adjustment costs 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.

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 Moody's series of yields on Aaa long-term corporate bonds. The corresponding data for Canada was obtained from the

[13] Chained 2000 dollars.

Canadian Central Bank. It is the series of yields on long-term bonds calculated by Scotia Capital INC.

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 corporate bond yields varies only through time, since we have no information on yields per industrial sector, but, in light of our stylized model, the cross-sectional variation in the cost of funds may have interesting implications for factor accumulation and productivity. Finally, the series for the United States and Canada are based on yields of 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 we do not have information on equity returns by manufacturing industry in Canada. 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 and other variables.

A. Baseline Regressions

Our baseline specification for the regression equation is represented by;

$$\Delta\% V_{s,t} = d_t + d_s + \gamma * MRZ_s * cost_{s,t} + e_{s,t} \tag{3}$$

where V represents alternative dependent variables—with special interest for TFP—for sector *s* in year *t*, d_t is a dummy for year *t*, d_s is a dummy for sector *s*, MRZ_s is our index of dependence on external finance for sector *s*, $cost_{s,t}$ is the cost of funds for sector *s* at date *t*, and $\text{e}_{s,t}$ is the residual. The focus is on the sign and magnitude of the estimated γ, which captures the differential impact of changes in the cost of finance on the growth rate of V.

Table 3 presents the results when V represents industry GDP, TFP, capital-labor ratios, the size of the labor force, and capacity utilization, respectively. Intuitively, industry GDP declines in response to increases in the yields on corporate bonds. The estimated coefficient of -2.12 implies that a 100 basis point increase in the cost of funds reduces GDP growth in a sector with an average degree of dependence on external finance by around 0.6 percentage point compared to a sector that does not depend on external funds. The reader might be concerned that such an estimate potentially overstates the power of monetary policy to affect manufacturing output. However, the cost of funds here is represented by the yields on long-term corporate bonds, not short-term securities. To the extent that long-term securities are less sensitive to changes in the fed funds rate or its Canadian equivalent, the apparent power of monetary policy is substantially weakened. In reality, there are probably important sources of upward bias in the estimated coefficient, making the result even stronger. For example, not only production depends on external finance, but demand does so as well. If the demand for sectors that depend more on finance is also more sensitive to credit availability, a demand shock for those sectors has a large impact in demand for funds, driving up interest rates. This mechanism creates an upward bias in our estimation of γ in regression 3.[14] With these caveats in mind, table 3 presents evidence that the production of sectors that depend more on external funds is more sensitive to the cost of finance.

Table 3 also indicates that a higher dependence on external finance makes labor and capacity utilization more sensitive to financial shocks, which is naturally understood. Interestingly, though, the cost of funds has no significant effect on the capital-labor ratio. Hence, it seems that increases in the cost of finance induce sectors to scale back, but not to change their relative use of factors.

Most importantly for our purposes, we can see from Table 3 that TFP growth is negatively affected by increases in yields. The estimated γ of -0.96 implies that a one-standard deviation increase in the yields on long-term corporate bonds reduced TFP growth in sectors with average dependence on external finance by 0.25 percentage point more than in a benchmark sector without any dependence on external finance. The economic significance of this result is unquestionable. 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 also investigate whether there are significant differences in the relation between TFP growth and the cost of funds among U.S. and Canadian industries. We rewrite regression 3 including a dummy variable DCAN for observations of Canadian industries:

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[14] Of course, this bias is only relevant if one wants to give a structural interpretation to the estimated coefficient.

$$\Delta\%Y_{s,t} = d_t + d_s + \gamma_0 * MRZ_s * cost_{s,t} + \gamma_1 * DCAN * MRZ_s * cost_{s,t} + e_{s,t}$$

As can be seen from Table 4, there seems to be no distinction between the two countries, since the estimated γ_1 is small and statistically insignificant.

The central message emerging from the initial regressions is that financial shocks have a statistically significant and economically meaningful impact on TFP growth. Sectors that depend more on external finance suffer more the effects of swings in the cost of capital in terms of productivity growth. To the extent that dependence on finance is relatively exogenous to factors or productivity, this relation is more than pure co-movement between variables. We are inclined to conclude that the cost of funds is an important determinant of total factor productivity growth at the business cycle frequency.

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, then variations in demand and the scale of operation will directly affect measured TFP. In particular, increasing returns to scale could explain our findings. If demand for the output of sectors that depend more on finance is also more sensitive to credit availability, financial shocks will affect more the demand for those sectors, impacting TFP growth calculated under the assumption of constant returns. In this case, say, an increase in the cost of funds reduces demand, which reduces the scale of operation of plants and, as a consequence, their efficiency. The strength of these events will be higher the higher the responsiveness of demand to credit conditions.

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

$$Y_s = \tilde{A}_s \left(K_s^{\psi_s} L_s^{1-\psi_s} \right)^{\rho}$$

where $\tilde{A}_s$ is the industry's true TFP and ρ is a parameter that captures the degree of returns to scale. 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

$$\Delta\% A_s = \Delta\% \tilde{A}_s + \left(\alpha_s - \rho\psi_s\right)\Delta\%\left(\frac{K_s}{L_S}\right) + \left(\rho - 1\right)\Delta\% L_s$$

Clearly, the bias in measured TFP growth depends both on the returns to scale and the size of operation of industries (represented by $\Delta\% L_s$), which could be affected by movements in demand that results from changes in credit availability.

In order to control for this possibility, we redo the regressions of TFP growth including, among the explanatory variables, the growth in the capital labor ratio and the growth in labor:

$$\Delta\% TFP_{s,t} = d_t + d_s + \gamma * MRZ_s * cost_{s,t} + b_0 * \Delta\%\left(\frac{K_{s,t}}{L_{s,t}}\right) + b_1 * \Delta\% L_{s,t} + e_{s,t} \qquad (4)$$

Table 5 shows that the negative impact of the cost of funds on TFP growth is preserved, albeit its magnitude is reduced. Now, a one standard-deviation increase in the yields on corporate bonds reduces annual TFP growth in a sector with average dependence on external finance by 0.16 percentage point more than in a benchmark nondependent 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 scale, while a negative number points towards decreasing returns. From table 5, there is indication that industries display fairly constant returns to scale.[15]

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 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.[16] The basic conclusions remain valid in all cases.[17]

[15] Basu (1996) also rejects the idea that increasing returns to scale could account for the procyclicality of productivity in the United States.

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

[17] The results are available upon request.

Finally, TFP growth for the U.S. petroleum industry is much more volatile than for other industries, which could affect our results significantly (see Figure 3). Thus, we reestimate the regressions excluding the observations for the U.S. petroleum industry only and found that shocks to funding costs still have statistically significant effects on TFP growth.[18] Actually, the effect seems stronger once one controls for returns to scale.[19]

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—the ones relevant for economic decisions.

To verify the strength of our findings, we reestimate the main regressions using a proxy for the cost of equity instead of yields on corporate bonds. In the entire section, we restrict the analysis to the United States only, since the required data on returns by industry portfolio is 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] NAICS code 324.

[19] The results are available upon request.

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[20] 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.[21] 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.[22] 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.[23]

[20] 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.

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

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

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

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 4th and 5th decile portolios 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 either high future returns, high 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

The baseline regression is once again represented by

$$\Delta\%TFP_{s,t} = d_t + d_s + \gamma * MRZ_s * cost_{s,t} + e_{s,t}$$

Because 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.[24]

Table 6 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. There is again strong evidence that increases in the cost of funds have a negative impact on TFP growth. Interestingly, the effect is much stronger when we use our measure of expected returns on equity, since the estimated γ is more than twice the coefficient estimated using yields on corporate bonds. It implies that a one-standard deviation increase in the dividend-yield on the market portfolio predicts a decline in annual TFP growth of a sector with an average dependence on external finance of approximately 0.46 percentage point more than in a benchmark sector.

[24] Results are essentially identical using a two-period lag.

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 lack of variability in the explanatory variable might reduce the correlation between yields on bonds and sectoral TFP, biasing down the estimated γ.

Once more, returns to scale are hardly an explanation for the findings. In an attempt to control for the scale of industries, we include the growth rate of capital-labor ratios and the labor force in the regression.

$$\Delta\%TFP_{s,t} = d_t + d_s + \gamma * MRZ_s * cost_{s,t} + b_0 * \Delta\%\left(\frac{K_{s,t}}{L_{s,t}}\right) + b_1 * \Delta\%L_{s,t} + e_{s,t}$$

Table 7 shows that controlling for the scale of industries only reinforces the negative link between the cost of funds and TFP growth, since the estimated γ increases over 2. This high number suggests that a one-standard deviation increase in the dividend-yield on the market reduces annual TFP growth for a sector with average dependence on external finance by roughly 0.6 percentage point more than a benchmark sector. This is almost half the average growth rate for the manufacturing sector as whole in our sample.

VI. Discussion

The empirical evidence strongly suggests that increases in the cost of finance have a negative effect on total factor productivity. 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 findings.

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 a 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 γ, making our central result, the negative value we estimate, even stronger.

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. 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. Hence, for the reverse causality story to have a bite, one has to complement it with an explanation of why the cost of funds in general goes up precisely at the moment the sectors that depend more on finance have low productivity. In other words, it is the correlation between the impact of the 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.

From a theoretical perspective, how can we interpret this negative relationship between financial shocks and TFP growth? The stylized neoclassical model presented in section 2 suggests that increases in the overall component of the cost of funds should have a positive impact on sectoral TFP, the more so the higher the dependence on external finance. The intuition is that shocks that affect symmetrically different firms level the playing field of access to funds, inducing a more efficient allocation of factors. According to the model, for TFP to decline, shocks shall increase the dispersion of the idiosyncratic component of the cost of finance. Hence, the basic neoclassical model can be reconciled with the empirical findings to the extent that increases in general measures of the cost of finance are accompanied by higher dispersion of firm specific distortions.

Our findings can also be explained by the "reverse-liquidationist" view of Caballero and Hammour. It postulates that tighter credit conditions create frictions in the process of creative destruction, with negative consequences for factor productivity. More specifically, the shortage of funds slows the activity of mergers and acquisitions, allowing inefficient plants to survive longer.

In a certain sense, the two approaches share a common root. They both suggest that the link between financial shocks and TFP results from the reallocation of factors across firms with different degrees of efficiency. This is the crux of the matter. Whether this reallocation involves creative destruction or simple changes in the scale of plants is, in our view, a secondary issue, especially for the events occurring at the business cycle frequency.

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. 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	0.20	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	0.40	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 and RZ, which are in levels)

Variable	Mean	Std. Dev.	Min	Max	Obs
TFP	1.59	5.99	-29.32	30.50	527
GDP	1.28	7.5	-24.18	35.98	527
Labor	-1.06	4.87	-15.65	23.38	527
Capital-Labor Ratio	1.82	5.02	-22.04	18.24	527
Capacity Utilization	0.01	4.25	-19.28	14.48	527
Yields	7.18	1.47	5.24	11.32	527
RZ	0.28	0.26	-0.08	0.96	527

Table 3. Baseline Regressions

Dependent Variable Growth Rates	GDP	TFP	KL	Labor	Capacity
Estimated γ	-2.12***	-0.96***	0.07	-0.49**	-0.90***
Std. Dev.	0.43	0.35	0.12	0.20	0.06
Probability	0.00	0.01	0.57	0.02	0.00

All regressions allow for heteroskedasticity and autocorrelation of the residuals.
* Significant at the 10% confidence level.
** Significant at the 5% confidence level.
*** Significant at the 1% confidence level.

Table 4. TFP Growth: The Canadian Dummy

Coefficient	Estimate	Std. Dev.	Probability
γ_0	-1.20***	0.44	0.01
γ_1	0.17	0.94	0.85

The regression allows for heteroskedasticity and panel-specific autocorrelation of the residuals.
*Significant at the 10% confidence level.
**Significant at the 5% confidence level.
***Significant at the 1% confidence level.

Table 5. TFP Growth: Returns to Scale

Coefficient	Estimate	Std. Dev.	Probability
Γ	-0.58***	0.17	0.00
b_0	0.25***	0.03	0.00
b_1	0.02	0.02	0.51

The regressions allow for heteroskedasticity and panel-specific autocorrelation of the residuals.
*Significant at the 10% confidence level.
**Significant at the 5% confidence level.
***Significant at the 1% confidence level.

Table 6. TFP Growth: Cost of Debt vs. Cost of Equity

Cost of Funds	Coefficient	Estimate	Std. Dev.	Probability
Equity	γ	-1.66***	0.10	0.00
Bonds	γ	0.73***	0.06	0.00

The regressions allow for heteroskedasticity and panel-specific autocorrelation of the residuals.
*Significant at the 10% confidence level.
**Significant at the 5% confidence level.
***Significant at the 1% confidence level.

Table 7. TFP Growth: Cost of Equity and Returns to Scale

Coefficient	Estimate	Std. Dev.	Probability
γ	-2.04***	0.05	0.00
b_0	0.41***	0.01	0.00
b_1	-0.18***	0.01	0.00

The regressions allow for heteroskedasticity and panel-specific autocorrelation of the residuals.
*Significant at the 10% confidence level.
**Significant at the 5% confidence level.
***Significant at the 1% confidence level.

APPENDIX B–FIGURES

Figure 1. Increase in the Cost of Finance and TFP

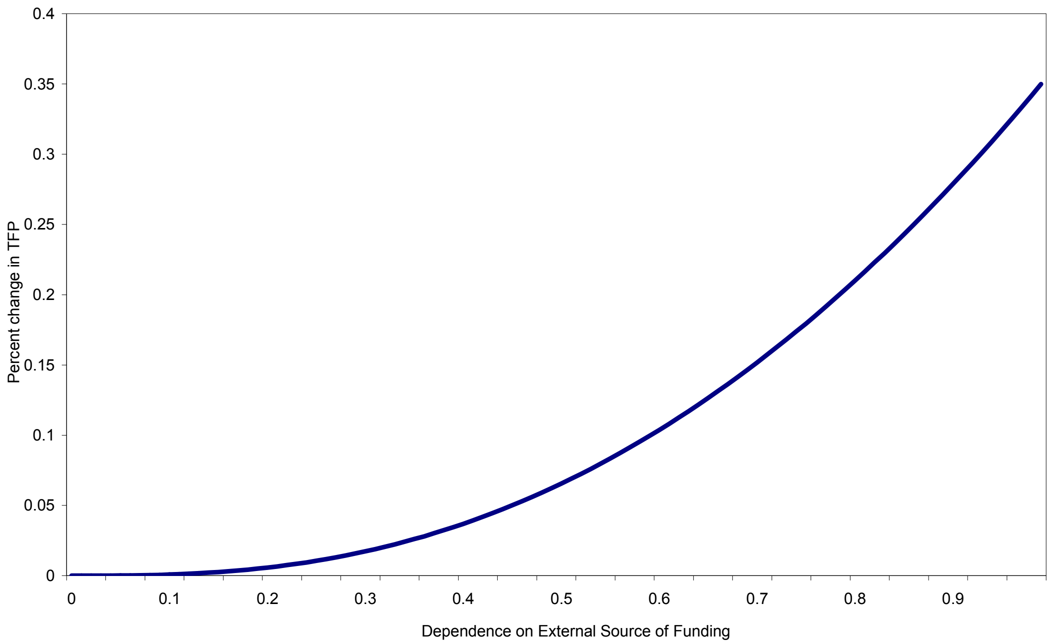


Figure 2. Increase in Heterogeneity and TFP

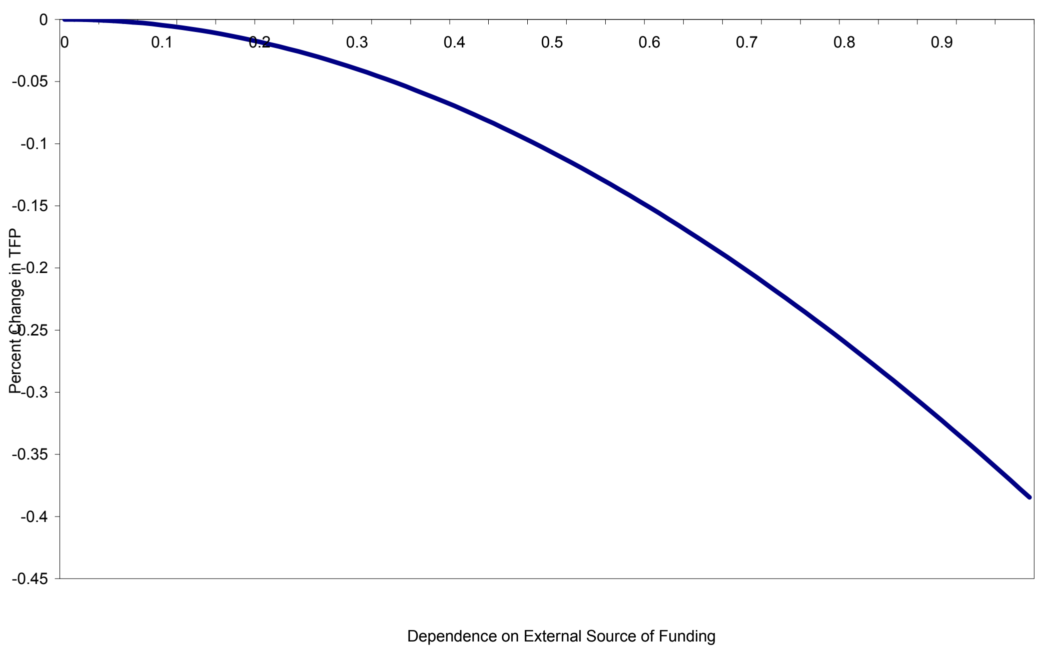
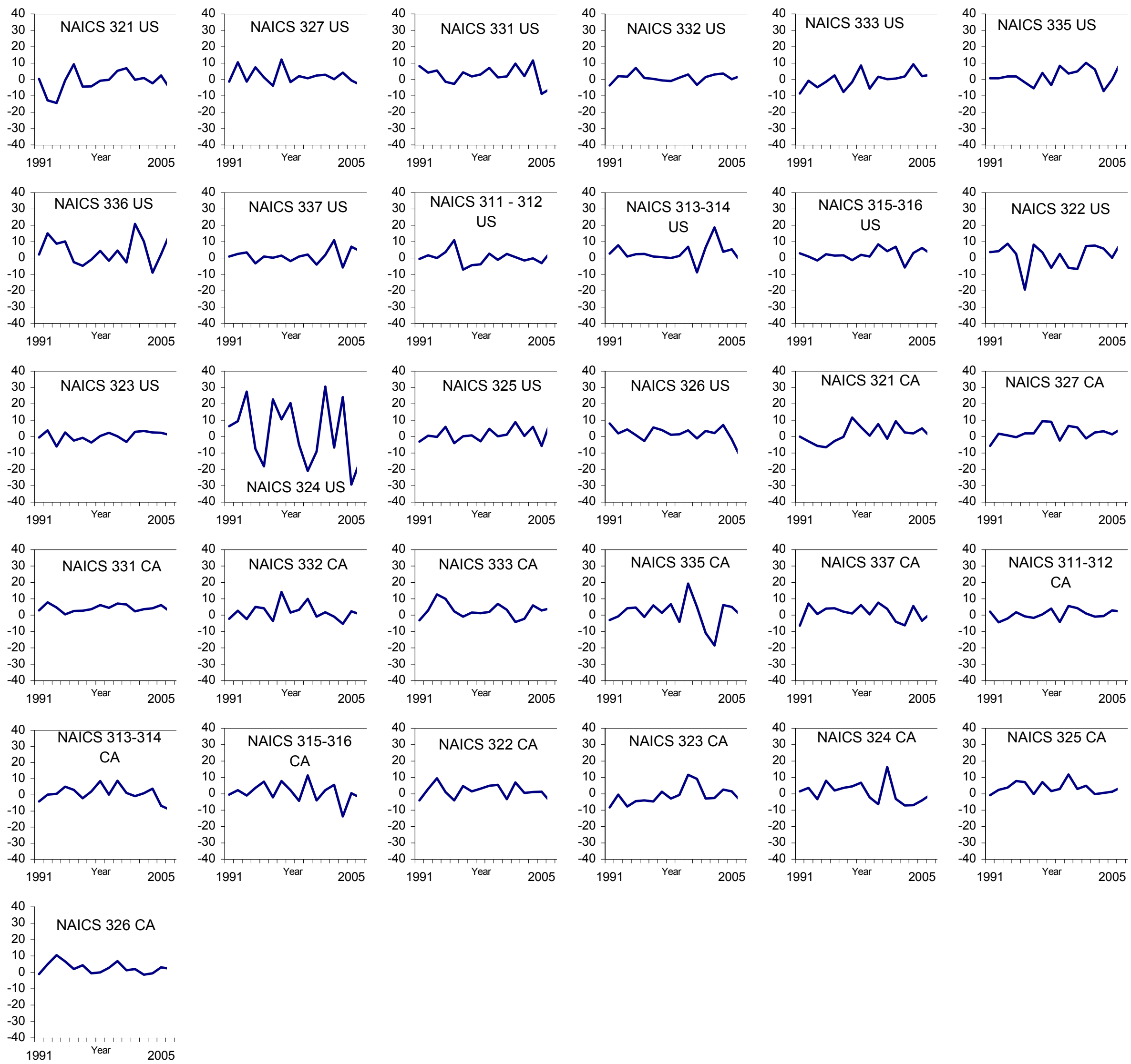


Figure 3. US and Canada TFP Growth, 1991-2007

(percent change in TFP, LH axis)



Appendix C–Calibration

In section 2, we conducted two comparative static exercises. In the first scenario, we considered the effects on TFP growth of an increase in the common component of interest rates $\bar{\tau}$, while in the second case we analyzed the effects of increases in the dispersion of the idiosyncratic component τ_{si}. The elasticity of substitution across goods σ is set to 1.2, while the sectoral component of interest rates τ_s is normalized to 0. Firm-specific TFP A_{si} is uniformly distributed over the [0.5,1] interval with 100 observations per industry. The parameter of dependence on external finance ϕ_s is uniformly distributed over the [0,1] interval, with 100 different industries.

In the first exercise, we assume that the idiosyncratic component τ_{si} is uniformly distributed over the [-0.15,0.15] interval for the 100 firms in each industry. Then we consider the effects of an increase in the common component of the cost of funds $\bar{\tau}$ from 0 to 0.4. In the second exercise, we set the common component equal to 0.1 and increase the dispersion of the idiosyncratic term: from no dispersion to uniform dispersion over the interval [-0.15,0.15].

The diagrams displayed in section 2 were constructed under the assumption that the distribution of firm-specific TFP was independent from the distribution of the idiosyncratic component of the cost of funds. As discussed in the text, we have also considered the cases of perfect positive and perfect negative correlation between the two variables, with virtually identical results in terms of TFP growth.

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