The Counteracting Effects of Credit Constraints on Productivity: Theory and Evidence

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Abstract

Financial constraints may have counteracting effects on aggregate innovation and growth. We develop a model that shows that, on the one hand, a decrease in financial constraints makes it easier for good innovators to further innovate, while, on the other hand, it allows less efficient incumbent firms to remain on the market, thereby discouraging entry and the reallocation of resources to more efficient firms. Our contribution stems from the combination of those two effects that have so far largely been studied on their own. Using a large French firm-level dataset and an unexpected exogenous shock to firm-level financial constraints, we identify these two counteracting effects. At the aggregate level, we find an overall concave effect of credit constraints on growth and offer an explanation for the dynamics behind the low constraints and low productivity growth that we observe in developed economies for already several years.

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1 Introduction

A whole body of research since the 1990s argues that lower financial constraints have a positive effect on economic growth and especially on innovation-based growth, with empirical prominent contributions by King and Levine (1993), Levine (1997) and Rajan and Zingales (1998). As described by Aghion et al. (2010), one channel could be R&D investment as if firms can choose between short-run capital investment and long-term R&D investment, a negative shock would hit R&D investment and innovation more in firms that are more credit constrained, with a detrimental impact on productivity growth. Several papers have empirically confirmed this channel, as for instance Aghion et al. (2012) on a large dataset of French firm (see also Levine 2005; Beck and Levine 2018 and Popov 2017 for surveys of this empirical literature). Some more recent empirical papers using individual firm datasets in the context of the financial crisis obtain the same type of results. For instance, Duval et al. (2017) and Manaresi and Pierri (2017), respectively on US and Italian firms show that higher financial constraints have a detrimental impact on productivity growth around the crisis. They highlight a similar channel, namely that firms that are exposed to financial constraints lower their investment, especially in assets that have a strong impact on productivity, such as R&D, ICT or intangible capital. On the theory side, models have been developed to show how financial development or lower credit constraints can foster innovation-led growth by reducing the costs of screening promising projects (e.g., see King and Levine 1993; and Aghion et al. 2009).

Another type of empirical literature shows that low real interest rates and financial constraints that existed before the financial crisis could contribute to explain the large productivity slowdown in southern European countries. The main channel of this impact is an increase of factor misallocation (see for instance Reis 2013, Gopinath et al. 2017 or Cette et al. 2016). Gopinath et al. (2017) show that the marginal product of capital has become more dispersed in southern Europe, including within manufacturing. Such a relationship is also empirically characterized on other types of data. For example, on industry data over a large set of countries, Borio et al. (2016) find that fast credit growth leads to lower productivity growth. Using data on about 260 US metropolitan statistical areas (MSA) over the period 2007-2014, Gropp et al. (2017) show that higher financial constraints increase cleansing mechanisms and job destruction with a positive impact on MSA average productivity growth. This literature suggests that due to lower financial constraints and real interest rates, the firms with the highest productivity did not crowd out the least efficient ones.[1] In other words, a decrease of credit constraints reduces the cleansing mechanisms.[2] Low productivity firms survive longer, which has a mechanical detrimental effect on average productivity growth. At the same time, it decreases the efficiency of factor allocation which has also a detrimental impact on the average productivity growth. Therefore, it appears that the existing literature provides two opposite relationships between financial constraints and productivity growth.

In this paper we associate these two types of relationships, both through a theoretical approach and an empirical one on a large dataset of French firms. Lower credit constraints can have both a positive impact through easier innovation financing and simultaneously a counteracting effect on innovation-led growth through less efficient resource allocation towards more innovative firms. Compared to the existing literature, the main originality of this paper is to associate the two relationships in the same approach.

In the first part of this paper, we extend the model of innovation-led growth and firm dynamics by Klette and Kortum (2004) as presented in Aghion et al. (2015), by introducing credit constraints into the model. In the Klette-Kortum framework,[3] innovation on any product line involves creative destruction on that line and is associated with firm dynamics in the following way. Firms are defined as a collection of production units. Successful innovation by an incumbent firm on a product line allows that firm to add that product line to the set of product lines it supplies; in other words, successful innovation by the incumbent firm allows that firm to expand. Successful innovation by another incumbent firm or by a new entrant on any of its current product lines leads the incumbent firm to shrink. Lower credit constraints (i.e. higher financial development) in this framework can have two opposite effects on aggregate innovation and growth. On the one hand, this helps good innovators to fully invest in innovation, which is good for aggregate innovation and growth. This is a direct investment effect of financial development. On the other hand, lower credit constraints make it easier for less efficient incumbent firms to remain on the market which, in turn, may discourage the entry and expansion of more efficient innovators, and thereby affect aggregate innovation and

[1]On the effects of financial exuberance or credit booms on productivity see also Gorton and Ordoez (2014), Cecchetti and Kharroubi (2015).

[2]Challe et al. (2016) propose another mechanisms. They build a model whereby easier financing conditions lead to "soft budget constraints". They show that more negative current accounts are correlated with a lower degree of rule of law, which weighs on economic growth, this relationship being particularly accurate in southern euro-area economies after the mid-1990s.

[3]See also Akcigit and Kerr (2010, 2018), and Acemoglu et al. (2018)

growth negatively. We refer to this as the reallocation effect of financial development. We show that these two counteracting effects of financial development result in financial development having an overall concave effect on aggregate innovation and growth, and that under reasonable assumptions the effect of financial development on innovation-led growth is an inverted U. In this case however, the downward part of the inverted U disappears when controlling for new firm entry.

In the second part of the paper we confront our theoretical predictions to the data. We use the French FiBEn firm-level database constructed by the Banque de France which provides information on firm size, firm-level production activities, and firms' balance sheet and P&L statements. In addition, we use information on credit access by firms, which we proxy by a variable called "Cotation" which rates firms according to their financial strength and capacity to meet their financial commitments. This "Cotation" is considered as a proxy for access to credit, as it is widely available to banks, consulted by them when granting a credit and used by the Eurosystem (European Central Bank and euro area national central banks) to assess the eligibility of a credit to be pledged against central bank refinancing. Then we regress firm-level TFP and the firm's probability to default and/or exit on this credit rating measure and, for the latter regression, its interaction with the firm's initial productivity. We find that the two channels linking financial development and economic growth in our theoretical framework are at work. A positive channel of improved access to credit, whereby firms become more productive through the easier financing of productivity-enhancing investments, co-exist with a negative channel whereby low-productivity firms exit less the market and maintain or even expand their share of production factors. Taken on an aggregate level, we show that financial development has an overall concave effect on innovation and growth. Beyond the straightforward explanation for the declining right hand-side of the concavity, we prove that its increasing left-hand side operates mainly through firm dynamics: at low but increasing constraints, as firms that had a low productivity become less productive and exit more the market, the positive reallocation channel overtakes the negative one and leads to more aggregate innovation and economic growth. We use a quasi-experiment, an unexpected decrease in credit constraints in 2012, related to a change in "Cotation" eligibility of credit collateral to the Eurosystem refinancing, to eliminate endogeneity problems and the subsequent statistical biases. Estimates of the impact of this shock confirm the results obtained and commented before.

The paper is organized as follow, section 2 present our theoretical framework, section 3 present the data, the empirical strategy and our main empirical motivations, section 4 presents our results and section 5 concludes.

2 A model of firm dynamics and growth with credit Constraints

In this section we introduce credit constraints in the Klette and Kortum (2004) model. We closely follow the presentation of Klette-Kortum in Aghion et al. (2015). In this framework: (i) there is entry, growth and exit of firms; (ii) innovations come from both entrants and incumbents; (iii) a firm is defined as a collection of production units; (iv) a firm expands by innovating on a new random product line, thereby displacing the incumbent producer on that line; (v) a firm shrinks when another producer innovates on one of its current product lines. Hence creative destruction is the central force that drives innovation, firm growth, entry and exit in this model.

2.1 The setup

Time is continuous and a continuous measure L of individuals work either as production workers, or as R&D scientists in incumbent firms, or as R&D scientists in potential entrants. The intertemporal utility function of the representative consumer is logarithmic:

$$U = \int_0^\infty \ln c_t . e^{-\rho t} dt,$$

so that the household's Euler equation is $g_t = r_t - \rho$.

The final consumption good is produced competitively using a combination of intermediate goods according to the following production function

$$\ln Y_t = \int_0^1 \ln y_{jt} dj \tag{1}$$

where y_j is the quantity produced of intermediate good j.

Each intermediate good j is produced monopolistically by the most recent innovator on product line j. She produces using labor according to the linear technology:

$$y_{jt} = A_{jt} l_{jt}$$

where A_{jt} is the product-line-specific labor productivity and l_{jt} is the labor employed for production. This implies that the marginal cost of production in j is simply w_t / A_{jt} where w_t is the wage rate in the economy at time t.

A firm is defined as a collection of n production units (product lines). Firms expand in product space through successful innovations. To innovate, firms combine their existing knowledge stock that they accumulated over time (n) with scientists (S_i) according to the following Cobb-Douglas production function

$$Z_i = \left(\frac{S_i}{\zeta} \right)^{\frac{1}{\eta}} n^{1-\frac{1}{\eta}} \tag{2}$$

where Z_i is the Poisson innovation flow rate, $\frac{1}{\eta}$ is the elasticity of innovation with respect to scientists and ζ is a scale parameter. Note that this production function generates the following R&D cost of innovation

$$C(z_i, n) = \zeta w n z_i^{\eta}$$

where $z_i \equiv Z_i / n$ is the per-line *innovation intensity* of the firm.

When a firm is successful in its current R&D investment, it innovates over a random product line $j' \in [0, 1]$. Then, the productivity in line j' increases from $A_{j'}$ to $\gamma A_{j'}$. The firm becomes the new monopoly producer in line j' and thereby increases the number of its production lines to $n + 1$. At the same time, each of its n current production lines is subject to the *creative destruction* x by new entrants and other incumbents. Therefore during a small time interval dt, the number of production units of a firm increases to $n + 1$ with probability $Z_i dt$ and decreases to $n - 1$ with probability $nxdt$. A firm that loses all of its product lines exits the economy.

2.2 Solving the model without credit constraints

We proceed in two steps. First, we solve for the static production decision and then turn to the dynamic innovation decision of firms, which will determine the equilibrium rate of productivity growth.

2.2.1 Static production decision

Given the logarithmic production technology for the final good, from Aghion and Howitt (2009) and Aghion et al. (2015) we know that the final good producer spends the same amount Y_t on each variety j. As a result, the final good production function in (1) generates a unit elastic demand with respect to each variety: $y_{jt} = Y_t/p_{jt}$. Combined with the fact that firms in a single product line compete Bertrand with a competitive fringe endowed with the previous technology on that line, this implies that a monopolist with marginal cost w_t/A_{jt} will follow limit pricing by setting its price equal to the marginal cost of the previous innovator $p_{jt} = \gamma w_t/A_{jt}$. The resulting equilibrium quantity and profit in product line j are:

$$y_{jt} = \frac{A_{jt}Y_t}{\gamma w_t} \text{ and } \pi_{jt} = \pi Y_t. \tag{3}$$

where $\pi \equiv \frac{\gamma-1}{\gamma}$. Finally the equilibrium demand for production workers by the intermediate producer on each product line j, is simply

$$l_j = Y_t/\left(\gamma w_t\right).$$

2.2.2 Dynamic innovation decision

Let $V_t(n)$ denote the market value of an $n-$product firm at date t. Then $V_t(n)$ satisfies the Bellman equation:

$$rV_t(n) - \dot{V}_t(n) = \max_{z_i \geq 0} \left\{ \begin{array}{c} n\pi_t - w_t \zeta n z_i^{\eta} \\ +nz_i \left[V_t(n+1) - V_t(n)\right] \\ +nx\left[V_t(n-1) - V_t(n)\right] \end{array} \right\}. \tag{4}$$

The intuition behind this equation can be explained as follows. The firm obtains total profit $n\pi_t$ from its n product lines and invests in total $w_t\zeta n z_i^{\eta}$ in R&D. It then innovates with flow probability $Z_i \equiv nz_i$, in which case it gains $V_t(n+1) - V_t(n)$. In addition, the firm loses each of its product lines through creative destruction at rate x, thus overall the firm will lose a production line at flow rate nx, leading to a loss of $V_t(n) - V_t(n-1)$.

It is a straightforward exercise to show that the value function in (4) is linear in the number of product lines n and also proportional to aggregate output Y_t, with the form:

$$V_t(n) = nvY_t,$$

where $v = V_t(n)/nY_t$ satisfies (see Aghion et al., 2015):

$$v = \frac{\pi - \zeta \omega z_i^{\eta}}{\rho + x - z_i}. \tag{5}$$

The equilibrium innovation decision of an incumbent is simply found through the first-order condition of (4)

$$z_i = \left(\frac{v}{\eta\zeta\omega}\right)^{\frac{1}{\eta-1}}. \tag{6}$$

As expected, innovation intensity is increasing in the value of innovation v and decreasing in the labor cost ω.

2.2.3 Entrants

Potential entrants innovate upon an existing line by factor γ by hiring ψ scientists. It then starts out as a single-product firm. Free-entry implies that in equilibrium the value of a new entry $V_t(1)$ be equal to the innovation cost of innovation ψw_t, i.e.

$$v = \omega\psi. \tag{7}$$

Let us denote the entry rate per existing line by z_e. using the fact that the rate of creative destruction on each existing line is equal to the entry rate plus the rate at which some incumbent firm innovates on that line, we have:

$$x = z_i + z_e.$$

This, together with (5) , (6) and (7) , yields the equilibrium entry rate and incumbent innovation intensity:

$$z_e = \frac{\pi}{\omega\psi} - \frac{1}{\eta}\left(\frac{\psi}{\eta\zeta}\right)^{\frac{1}{\eta-1}} - \rho \quad \text{and } z_i = \left(\frac{\psi}{\eta\zeta}\right)^{\frac{1}{\eta-1}}.$$

2.2.4 Labor market clearing

The model is closed by the labor market clearing condition:

$$L = \frac{1}{\gamma\omega} + \zeta\left(\frac{\psi}{\eta\zeta}\right)^{\frac{\eta}{\eta-1}} + [\frac{\pi}{\omega} - \zeta\left(\frac{\psi}{\eta\zeta}\right)^{\frac{\eta}{\eta-1}} - \psi\rho] \tag{8}$$

where: (i) the first term on the RHS of (8) is the aggregate demand for manufacturing labor by all intermediate good producers (recall that there is a continuum of mass one of intermediate product lines and that all these lines have the same labor demand $\frac{1}{\gamma\omega}$); (ii) the second term is the aggregate employment ζz_i^{η} of scientists by incumbent firms; (iii) the third term is the aggregate employment ψz_e of scientists by entrants.

This equation yields:

$$\omega = \frac{w_t}{Y_t} = \frac{1}{L+\rho\psi}$$

2.2.5 Equilibrium growth rate

Innovation occurs on each line at flow rate of $x = z_i + z_e$. And whenever an innovation occurs on a product line labor productivity on that line is multiplied by γ. this yields the following expression for the equilibrium growth rate in the absence of credit constraints

$$\begin{aligned} g &= x\ln\gamma \\ &= \left[\left(\frac{\gamma-1}{\gamma}\right)\frac{L}{\psi} + \left(\frac{\eta-1}{\eta}\right)\left(\frac{\psi}{\eta\zeta}\right)^{\frac{1}{\eta-1}} - \frac{\rho}{\gamma}\right]\ln\gamma. \end{aligned}$$

2.3 Introducing credit constraints

We model credit market imperfections by assuming that intermediate firms cannot invest more than μ times their current market value in innovation. Thus a firm of size n at date t cannot spend more than $\mu V_t(n)$ in R&D at date t. More formally, we impose the constraint:

$$\zeta w n z_i^{\eta} \leq \mu V_t(n) = \mu n v Y_t$$

or equivalently

$$z_i \leq \left(\frac{\mu v}{\zeta\omega}\right)^{1/\eta}. \tag{9}$$

We shall focus on the case where potential entrants have accumulated enough wealth that the credit constraint is not binding on them. [4]

We shall then be interested in the case where (9) is binding (if it is not binding then we are back to our previous analysis). Then, using the above Bellman equation, one can show that:

$$(\rho + z_e)v = \pi - \zeta\omega\left(\frac{\mu v}{\zeta\omega}\right)$$

or

$$z_e = \frac{\pi}{\omega\psi} - \mu - \rho$$

The labor market clearing condition becomes:

$$L = \frac{1}{\gamma\omega} + \psi z_e + \zeta z_i^\eta$$

which again yields

$$\omega = \frac{1}{L + \rho\psi}.$$

Let us take $\eta = 2$. Then equilibrium growth rate is equal to:

$$g = x \ln\gamma = [z_e + z_i]\ln\gamma$$

that is

$$g = \left[\frac{\pi}{\omega\psi} - \mu - \rho + \left(\frac{\mu\psi}{\zeta}\right)^{1/2}\right]\ln\gamma \tag{10}$$

We see that μ has two counteracting effects on g : on the one hand a higher μ, i.e less credit constraints, increase innovation intensity by incumbents, this is the second term on the RHS of

[4] Thast is, we shall concentrate on parameter values such that:

$$\mu v + B > \omega\psi,$$

where B is the initial output-adjusted wealth of a potential entrant. We will see below that we still have

$$\omega = \frac{1}{L + \rho\psi}$$

under this assumption, so that the above condition can be reexpressed as:

$$\mu v + B > \frac{\psi}{L + \rho\psi}.$$

(10): this corresponds to a positive *investment effect* of relaxing credit constraints; on the other hand, a higher μ reduces innovation intensity by entrants $z_e = \frac{\pi}{\omega\psi} - \mu - \rho$: this corresponds to a negative *reallocation effect.*

These two effects combined produce a concave relationship between μ and g. Then it is easy to extend the model so as to obtain an inverted-U relationship between μ and g. For example if the innovation size γ_e for entrants is strictly larger than the innovation size γ_i for incumbents, then the equilibrium growth rate g, equal to

$$g = (\frac{\pi}{\omega\psi} - \mu - \rho) \ln \gamma_e + \left(\frac{\mu\psi}{\zeta}\right)^{1/2} \ln \gamma_i$$

satisfies:

$$\begin{aligned} \frac{dg}{d\mu} &> 0 \text{ for } \mu \text{ small;} \\ \frac{dg}{d\mu} &< 0 \text{ for } \mu \text{ close to } \frac{\psi}{4\zeta}, \end{aligned}$$

where $\mu = \frac{\psi}{4\zeta}$ is the maximum value of μ for which the credit constraint is binding.[5]

2.4 Predictions

The main predictions from the model are:

Prediction 1: The relationship between financial development ($\mu\%$) and growth is concave, and can be inverted-U shaped.

Prediction 2: The downward part of the inverted U disappears when controlling for new firm entry.

We now confront these predictions to French sectoral and firm-level data.

[5]When $\gamma_e = \gamma_i = \gamma$, we have

$$\frac{dg}{d\mu} \propto -1 + \left(\frac{\psi}{\zeta}\right)^{1/\eta} \frac{1}{\eta} \mu^{1/\eta - 1}$$

Whenever the credit constraint for incumbents R&D is binding, we have:

$$\left(\frac{\mu\psi}{\zeta}\right)^{1/\eta} \leq \left(\frac{\psi}{\zeta\eta}\right)^{\frac{1}{\eta-1}}$$

which implies that

$$\frac{dg}{d\mu} \geq 0$$

thus there is no inverted-U in that case. expression

3 Data and Main Facts

3.1 Firm- and Sector-level Data

Our main source of data comes from FiBEn. FiBEn is a large French firm-level database constructed by the Bank of France based on fiscal documents, including balance sheet and P&L statements, and contains detailed information on firms' activities and size. FiBEn includes French firms with annual sales exceeding $750,000$ euros or with outstanding credit exceeding $380,000$ euros. This database can be consistently used from 1989 and is complete up to 2014. We shall however restrict attention to a subset of this period –in most cases 2004-2014– due to other data availability. We also restrict the sample to private manufacturing firms because these are the firms from which we can measure productivity more accurately.[6] Table 1 gives the medians of key variables for our dataset starting in 2004.

While Table 1 showed yearly median values over all our sample, Table A1 in Appendix A gives sector level median of key variables. To produce this table, we have augmented our firm level dataset with data for the manufacturing sector taken directly from the French National Statistical Office (INSEE) on entry rate, exit rate and creative destruction rate of establishments (where the latter is defined as the mean of entry and exit rate, following e.g. Aghion et al., 2016). The last three columns of Table A1 give the average value for these three measures over the years 2004-2014 for the 21 manufacturing sectors in our data.

3.2 The Bank of France Rating and Firm Credit Constraints

In addition to firm balance sheet data, we have detailed information on new loans, namely on the interest rates and quantities of new investment loans from the database $MContran$, but they are unfortunately only available from a small random sample of firms.

For this reason, we will mostly rely on a proxy that measures access to credit by firms: the credit "Cotation" of the Bank of France. The credit "Cotation" is a rating that classifies companies according to their financial strength and capacity to meet their financial commitments at a three-year horizon. A firm can be rated from 3^{++} to 9 (and P in case of collective insolvency proceedings), but we have gathered them into 3 different categories for the sake of simplicity: category A (corresponding to rating levels 3^{++}, excellent capacity to meet its financial commit-

[6] We further exclude the tobacco, processing and coke industries due to a limited amount of observations.

TABLE 1: DESCRIPTIVE STATISTICS FOR FIRMS IN THE MANUFACTURING SECTOR

Year	L	Y	Age	g	Firms
2004	17	808	15	2.54	25,399
2005	17	810	15	1.08	25,765
2006	16	818	16	1.66	26,828
2007	17	840	16	2.01	29,296
2008	17	839	17	-2.68	30,598
2009	18	889	19	-2.05	33,958
2010	18	892	19	1.26	34,910
2011	17	886	20	-0.20	35,261
2012	17	881	21	-0.91	34,815
2013	18	916	21	0.59	33,594
2014	18	928	22	1.37	33,047

Notes: This table reports the median level of employment (L), real value added in thousand euros (Y), age and TFP growth (g) for private manufacturing firms with annual sales exceeding $750,000$ euros or with outstanding credit exceeding $380,000$ euros from the years 2004 to 2014. The data has been trimmed for the top and bottom 1% of TFP growth values. TFP is calculated following Levinsohn and Petrin (2003). Source: *Fiben*.

ments to 4^+, rather strong capacity), category B (corresponding to ratings 4, correct capacity and 5^+, rather weak capacity) and category C (corresponding to ratings 5, weak capacity to P). Category A should be understood as a group of firms that are judged healthy by experts at the Bank of France, while category C comprises firms that are considered as having a weak capacity to meet their financial commitments, or have even entered a collective insolvency proceeding. This rating resorts to balance sheet based formula as rarely as possible with a strong preference for on-site visits and interviews. This rating is on average updated every 14 months, but can be updated more frequently in some cases. Each year, we associate each firm with its last known rating. Table 2 shows that firms in the best categories are larger, older and more productive than others. On average, firms rated in the worse category have about 9% chance to be liquidated in the near future. All these descriptive statistics are reported in Table 2.

All private banks can access this rating and use it in their provision of credit, to make a decision on their access to credit, the quantity granted and the interest rate offered. In addition, as we shall see later in our study, this credit rating is used by the Eurosystem to set the threshold below which corporate loans are eligible to be pledged as collateral by banks in their refinancing operations with the Eurosystem.

TABLE 2: Descriptive Statistics for the Bank of France Rating

Cat.	L	Y	Age	TFP	Liquidation	Obs.
A	18	1075	20	4.79	0.48	162,385
B	18	800	18	4.55	2.49	105,035
C	18	702	16	4.42	8.76	42,314
Total	17	871	18	4.65	2.60	338,541

Notes: This Table reports the median value of some variable for firms in different rating categories as described in section 3.2. L and Y stands for employment in total full time equivalent and value added in constant million of euros. TFP is calculated using the Levinsohn and Petrin (2003) methodology and is expressed in log. Finally, liquidation is the share of firms that will be liquidated in the near future, as explained in section 3.3

As this rating is widely available to banks, largely consulted and, as we shall see later, largely correlated with credit volume, we can use this rating as a proxy to assess firms access to external finance. Using our data on new loans, we test the relationship between ratings on the one hand and interest rates and quantities on the other hand by controlling for individual and sector characteristics.[7] Results are shown in Table 3 and suggests that firms in category A borrow at a lower rate and more than firms in categories B and C whether we consider short-term credit (with maturity below one year) or long-term credits. Differences between categories B and C are less clear in terms of quantities, but large and significant in terms of interest rate.

3.3 Liquidation

We complete our dataset with information drawn from a file that report all court-ordered liquidations (or winding-up) of a firm which has defaulted once or several times. Following this liquidation, the firm almost always exits the market and its assets are redistributed. We consider this has a sure indicator that the firm has exited our data because of its financial difficulties, and not for alternative reasons, some of them having little to do with its financial health (for example because the data producer did not report its balance sheet or because the owner retired). The Bank of France is responsible of a file that keeps track of all previous legal events regarding liquidation procedures and we therefore cover comprehensively the winding-up

[7] We have selected financial instruments and non-subsidized loans in order to avoid the noise made by other types of loans.

TABLE 3: RATING, INTEREST RATES AND QUANTITIES BORROWED

Dependent variable Credits	**r** Short Term	**r** Long Term	**log(Q)** Short Term	**log(Q)** Long Term
Rating category				
A	-0.348***	-0.400***	0.250***	0.311***
	(0.024)	(0.031)	(0.046)	(0.070)
B (ref)				
C	0.312***	0.280**	-0.026	0.012
	(0.052)	(0.121)	(0.073)	(0.164)
$Log(L_{t-1})$	-0.085***	-0.112***	0.671***	0.430***
	(0.013)	(0.018)	(0.031)	(0.042)
Age	-0.002***	-0.001	-0.001	-0.001
	(0.001)	(0.002)	(0.002)	(0.002)
Fixed Effects	$s \times t$	$s \times t$	$s \times t$	$s \times t$
R^2	0.675	0.628	0.354	0.310
Observations	5761	1458	5761	1458

Notes: This table reports results from a regression of the price and quantity of new loans on a dummy for being in each of the rating categories that are defined in the text. Columns 1 and 3 take information from short term loans (maturity $<$ 1 year) while columns 2 and 4 only consider long term loans. Estimates are obtained using an OLS estimator. Heteroskedastic robust standard error, clustered at the sector level are reported in parentheses. All regressions include a sector $\times$ year fixed effects.

of firms with the exact year the firm ceased to exist. Unfortunately, when a firm is about to disappear because of its financial difficulties, it is very likely that it stops sending its balance sheet to the Bank of France a few years before disappearing. This raises a technical difficulty in our dataset because it is almost impossible to observe the firm in the years before its liquidation. We have therefore decided to create a binary variable that takes the value 1 the last year the firm appear in our database and providing it will be liquidated. For 90% of the firms, the gap between the year of the winding-up and the last balance sheet information date is less than 4 years and most of the cases it is equal to 2. In any case, we do not consider balance sheet information that are less than two years before liquidation.

Note that the Bank of France rating is a good indicator of liquidation risk, which is its main purpose. This is shown in Table 2 and described in more details in the annual evaluation of this rating (see Banque de France, 2017). Another way of seeing this is to consider all firms that are in the data in 2004. Among these firms, more than 30% of these that are in rating category C in 2004 will be liquidated by 2016, with a peak during the crisis, against less than 10% for the best rating.

3.4 Main Motivation

The model predicts an inverted U-relationship between credit constraints (captured by the inverse of μ) and TFP growth g. While the negative correlation between the two has already been widely documented in the literature (see introduction), the left-hand side of the inverted U is a less common result. One would ideally like to directly test this relationship, however, the two mechanisms are very different and the whole story can only be directly tested using (limited) sectoral data.

This is what we first test in the simplest possible way: each year and for each 2-digit manufacturing sector, we calculate the difference between the average rate of new credits and the EONIA which we denote as "Spread" in what follows. Here we seek to estimate the level of credit constraint at the sector level by looking at how this spread measures deviate from the sector average. Indeed, this spread reflects mainly the credit risk assessment of the sector by banks and hence their willingness to grant credit to firms in this sector. We therefore estimate the following model:

$$g_{s,t} = \beta_1 Spread_{s,t} + \beta_2 \left(Spread_{s,t}\right)^2 + \nu_s + \varepsilon_{i,t},$$

where $g_{s,t}$ is the sector TFP growth and ν_s is a sector fixed effect. Estimates presented in the first column of Table 4 show that, as expected, β_1 is positive and β_2 negative, which is consistent with the prediction of an inverted-U relationship between productivity growth and credit constraint. Next, to give more support to our results, we split sectors into those that are above or below the median in terms of external financial dependence. A financially dependent sector will be one that is above the dependence indicator's median based on two different indicators: (i) the Rajan and Zingales (1998) indicator constructed as the ratio of externally financed capital expenditure over total capital expenditure for US manufacturing firms, where the former is calculated as the difference between total capital expenditure and cash flow from operations. It is denoted as "RZ" throughout the paper; (ii) following Aghion et al. (2017), we construct a second indicator as the US manufacturing firms' labor cost to sales ratio from the NBER-CES manufacturing industry database. It is denoted as "US" throughout the paper. The inverted-U relationship turns out to be significant only for sectors with a high external financial dependence ratio. The peak of the inverted-U is at the left of the sector distribution, which means that over the period, the negative impact of high spread on TFP growth dominated with regard to the cleansing effect. However, the period may also be specific, with the credit demand collapse dominating the effect of a would-be credit supply crunch during the financial crisis (Kremp and Sevestre 2013) . The peak of the inverted-U is also country-specific and depends in particular on the regulation of competition, for which France does not rank well among OECD countries (Koske et al. 2015).

TABLE 4: Sectoral interest rate and productivity

Dependent Variable	Sectoral TFP growth				
Dependence Indicator (EFDI)	All	RZ, high	RZ, low	US, high	US, low
Spread	3.206*	4.208	1.812	4.734**	1.497
	(1.728)	(2.550)	(2.571)	(1.974)	(2.820)
Spread Squared	-1.194**	-1.577**	-0.675	-1.664***	-0.665
	(0.475)	(0.709)	(0.699)	(0.525)	(0.792)
Fixed Effects	Sector	Sector	Sector	Sector	Sector
R^2	0.297	0.436	0.126	0.421	0.197
Observations	198	108	90	99	99

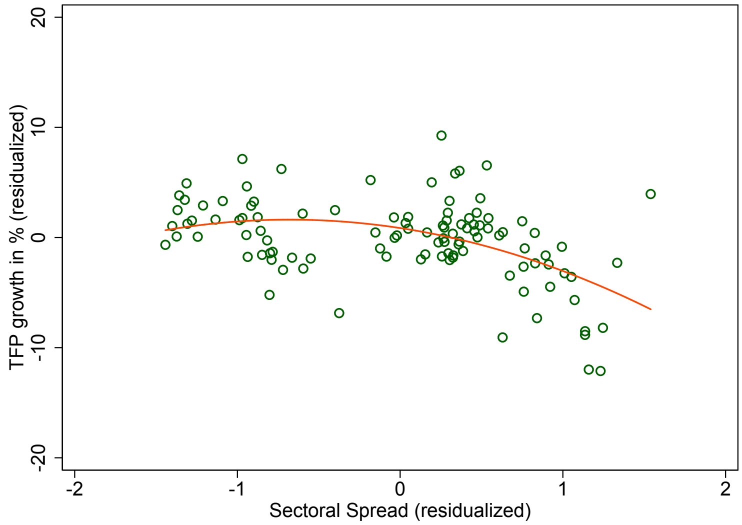
Notes: The dependent and independent variables are calculated as means per sector and year. All regressions include sector fixed effects. Heteroskedasticity sector standard errors are reported in parentheses.

Figure 1 plots for each sector associated with a RZ value of 1 and each year, the average TFP growth and spread both residualized on a sector fixed effects. The quadratic fit line is also reported and show the inverted U shape relationship what was already presented in Table 4.

3.5 Empirical Strategy

As argued before, directly testing the inverted U shape relationship between μ and g with firm level data poses an empirical difficulty. Indeed, the mechanism through which more constrained firms suffer from lower TFP gains stems from the fact that they have less investment possibilities and more difficulties to meet their financial commitments. This can be tested directly, providing we find a good measure of financial constraints that is not directly related to the firm past performance (see discussion below). However, the mechanism through which there can be an overall positive effect of credit constraints on productivity growth has to do with the cleansing effect of increasing selectivity of credit suppliers. This in turn will force some low performing

FIGURE 1: Sectoral spread and TFP growth



Note: Each dot represents a sector in a specific year from 2004 to 2014. TFP growth and spread have been residualized on a sector fixed effect. Manufacturing sector with an index of external financial dependence set to 1 (based on the RZ indicator). A list of the sectors is given in Table A1 in the Appendix.

firms to exit the market and raise average productivity, first because the market will be "purged" from low-productivity firms, and second because such cleansing will favor the entry of potential new and more productive competitors. To test this second effect with firm level data, we make use of our information on liquidation and check whether low-productivity firms are less likely to exit if they have an easy access to credit.

Endogeneity of credit access the main challenge in such empirical exercise is to address the question of reverse causality from past firm productivity performance to current access to external finance in a context of serial correlation in productivity series. In what follows, we will use our rating indicators as a measure of credit constraints, keeping in mind that these ratings suffer from the clear endogeneity problem that they are directly influenced by the firm balance sheet. However, in the process of rating a firm, the experts do not directly consider productivity and are mostly focused on the overall financial soundness of the firm resulting from its solvency, profitability, liquidity, etc... Similarly, banks put more weight on more direct information on the firm performance such as its profitability and to the current debt level (debt overhang). But financial ratios and profitability cannot be totally independent from productivity performances. So, we should consider the following results as simple correlations. In a second part of our empirical analysis, we will consider a regulatory discontinuity in the credit rating to address this endogeneity issue.

4 Results

As argued before, our empirical strategy proceeds in two steps: first we look at the direct impact of financial constraints on productivity, and second we look at how aggregate productivity can be affected by a relaxation of these constraints.

4.1 Firm-level Productivity Differential and Credit Constraint

In this first step, we look at the direct effect of the rating category on the productivity of the firm. We hence consider the following linear models:

$$tfp_{i,t} = \sum_{k} \alpha_k Cot_{i,t}^{(k)} + X_{i,t}\gamma + \nu_i + \nu_{s,t} + \varepsilon_{i,t}, \tag{11}$$

where $tfp_{i,s,t}$ is the log TFP level of firm i in sector s at t, $Cot_{i,t}^{(k)}$ is a dummy variable equal to 1 if the rating category of the firm i at t is equal to $k = (A, B, C)$, $X_{i,t}$ is a vector of observed characteristics of the firm, ν_i are firm controls and $\nu_{s,t}$ is a sector $\times$ year fixed effect. Because each firm$\times$year observation is in one of the three rating categories, we need to set one rating category as our reference to reduce the number of degrees of freedom. We set α_k to 0 when $k = B$ for this benchmark. Note that in this model, we are using a firm fixed effect (at least in our baseline specification) so we are mostly interested into long run variations of TFP compared to the firm average and our identification arises from firm that switch from one rating category to another. Estimates results of this relation are presented in the first 3 columns of Table 5. Column 3 uses a full set of fixed effects ν_i and $\nu_{s,t}$ and shows that having the best rating is associated with a productivity level that is 15% larger than a firm in the same sector which has a rating category B (again, compared to the firm average level).

In the next three columns of Table 5, we consider the growth rate of TFP as our dependent variable. Because firm in rating category C are significantly less productive than firms in rating category A, we also control for the lag value of the log of TFP in this model, so as to capture a natural catch up dynamics.[8] This model is estimated with OLS, but using the Arellano-Bond

[8]More specifically, we estimate the following model of β-convergence:

TABLE 5: RATING CATEGORIES AND TFP

Dependent variable	Individual TFP (log)			Growth rate of TFP		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Rating Category						
A	0.773	0.160***	0.151***	0.218***	0.154***	0.145***
	(0.478)	(0.003)	(0.003)	(0.052)	(0.004)	(0.004)
B (ref)						
C	0.378	-0.151***	-0.148***	-0.188***	-0.145***	-0.142***
	(0.641)	(0.005)	(0.005)	(0.046)	(0.006)	(0.005)
$Log(L_{t-1})$	0.423***	0.020**	0.009	0.424***	-0.009	-0.020
	(0.152)	(0.010)	(0.010)	(0.105)	(0.013)	(0.013)
Age	0.020	0.017***		-0.002***	0.015***	
	(0.022)	(0.001)		(0.000)	(0.001)	
$Log(TFP)_{t-1}$				-0.743***	-0.975***	-0.975***
				(0.182)	(0.023)	(0.023)
Fixed Effects	$s \times t$	i	$i + s \times t$	$s \times t$	i	$i + s \times t$
R^2	0.005	0.928	0.930	0.723	0.959	0.960
Observations	252,705	247,784	247,784	238,928	234,223	234,223

Notes: This table shows results from an estimation of the rating category and the log of TFP, both in level (columns 1 to 3) and in growth rate (columns 4 to 6). In the latter case, we include the lag of the log of TFP to capture catching-up dynamism. Coefficients are obtained using an OLS estimator and standard errors are heteroskedastic robust, clustered at the firm level and reported in parentheses.

GMM estimator delivers similar results. Our results are consistent with what was found in the first 3 columns, namely that the productivity of the firms in the rating category A grows significantly faster than the productivity of the firms having other ratings. We interpret these results as a direct impact of credit access on productivity level and dynamics which is in line with the investment effect of relaxing credit constraints highlighted in equation (10) of the theory. This interpretation implies that we can proxy for the supply of credit using firms' rating. Reassuringly, we obtain comparable results when we replace the credit rating by a more continuous measure that seeks to capture the extent to which the firm has a debt overhang, namely the ratio of the stock of debt over total non-financial assets. Another question is whether these results do not simply capture the fact that some firms are just poorly managed and have both a lower productivity and a lower propensity to meet their financial commitments. In such case, the rating category or any other measure of credit supply would be correlated with TFP but not because of an investment effect. This concern is at least partially alleviated by the use

$$\Delta tfp_{i,t} = \sum_k \alpha_k Cot^{(k)}_{i,t} + \beta tfp_{i,t-1} + X_{i,t}\gamma + \nu_i + \nu_{s,t} + \varepsilon_{i,t}, \tag{12}$$

of a firm fixed effect which captures time unvarying idiosyncratic quality of a firm. We further deal with the existence of such confounding factors and other potential endogeneity issues in section 4.3.

4.2 Productivity and risk of liquidation

To follow up on our theoretical model, we look in this second step at the probability of default for firms with different levels of credit constraints and at different levels of productivity. Our goal is to capture the negative reallocation effect that follows a relaxation of credit constraints. This reallocation effect is twofold: first it decreases aggregate productivity by preventing the exit of low productive firms, and second it prevents new producers to enter the market. Using our liquidation dataset, we directly test the first channel using the following model:

$$E_{i,t} = \sum_k \alpha_k Cot_k + \sum_k \beta_k Cot_k \times D_{i,t-1} + X_{i,t-1}\gamma + \nu_{s,t} + \varepsilon_{i,t}. \tag{13}$$

$E_{i,t}$ is a binary variable that takes the value 1 if the firm is about to be liquidated (see section 3.3). X includes both the logarithm of total employment of the firm and its age and $D_{i,t-1}$ is a firm level dummy for being below the sectoral 25% percentile in the productivity distribution at $t-1$.[9] To estimate this type of survival models, a panel fixed-effect estimator is not appropriate given that the dependent variable can only take the value 1 once, in the last observation. To correct for this, dedicated econometric methods have been developed. Before showing results with one of these models, let us first consider a linear model and estimate equation (13) using a simple OLS estimator.

Model (13) estimate results are shown in Table 6. Column 1 does not consider any interaction and simply reflects the fact that firms in rating category A are less likely to be liquidated than firms rated B and firms rated C. Column 2 adds the dummy D_i which is positively correlated with the likelihood of wining-up as we expect. The last three columns of Table 6 interact the dummy D_i with the rating category, as indicated is equation (13) respectively for all firms, and restricting to firms in sector with high and low RZ indicator.

[9]Table A2 in the Appendix consider a similar model but defining D_i using the productivity distribution in 2004 (in which case D_i is time invariant).

TABLE 6: LIQUIDATION AND RATING

Dependent variable	Liquidation at $t+2$ dummy				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
		All		High RZ	Low RZ
Rating Category					
A	-0.017***	-0.015***	-0.015***	-0.017***	-0.013***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
B (ref)					
C	0.054***	0.052***	0.047***	0.049***	0.044***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
$log(L_{t-1})$	-0.002***	-0.000*	-0.000*	-0.001**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Low Prod.		0.026***			
		(0.001)			
Rat. Cat. A $\times$ Low Prod			0.012***	0.014***	0.009***
			(0.001)	(0.002)	(0.002)
Rat. Cat. B $\times$ Low Prod			0.021***	0.025***	0.015***
			(0.002)	(0.002)	(0.003)
Rat. Cat. C $\times$ Low Prod			0.049***	0.058***	0.039***
			(0.004)	(0.005)	(0.005)
Fixed Effects	$s \times t$	$s \times t$	$s \times t$	$s \times t$	$s \times t$
R^2	0.035	0.038	0.038	0.039	0.039
Observations	306,051	306,051	306,051	194,781	110,984

Notes:

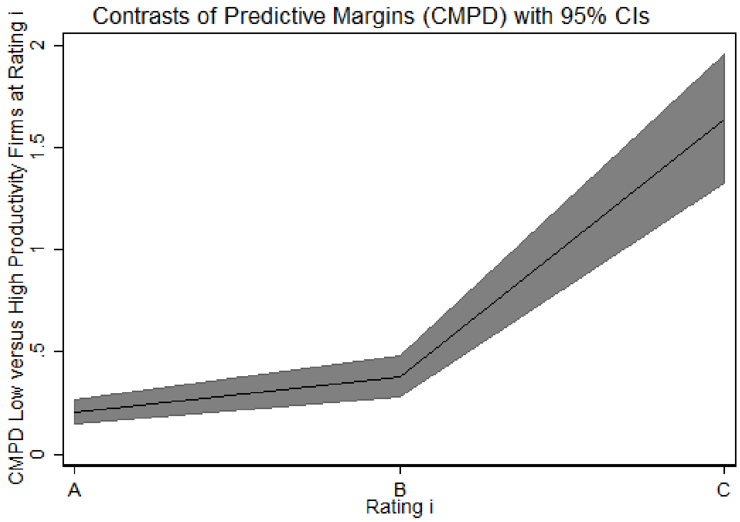
These results suggest that low productive firms are less likely to exit when they have easier access to credit, i.e. when they benefit from a category A rating. In addition, this effect is much stronger for firms that are in sectors that rely more on external finance. To put it differently, these results show that the relaxing of credit constraints allows low productive firms to remain in the market.

Recall that these estimates use an OLS estimator, and parameters should not be considered as marginal probabilities. We now turn to a parametric survival model to estimate coefficients of equation (13). More specifically, we consider a proportional hazards model where survival time follows a Weibull distribution. We hence estimate by maximum likelihood the following model:

$$\lambda(t|x_i) = \lambda p(\lambda t)^{p-1} e^{x_i'\beta}, \tag{14}$$

where $\lambda(t|x_i)$ is the hazard function (the instantaneous probability of liquidation a t for firm i), (p, λ) are the parameters of the Weibull distribution, x_i is the set of covariates presented in equation (13) and β the vector of corresponding coefficients. Because of the interacting terms, the results are rather complicated to read in a table and we prefer to report them graphically in Figure 2. More specifically, what Figure 2 represents is the difference between the predictive margins of liquidation of low productivity firms versus high productivity firms at any given rating $i \in A, B, C$. For an A rated firm, the difference is quite small meaning that low productive firms tend to survive more. However, as the constraints increase towards a C rating, the difference increases meaning that low productivity firms will exit relatively more than high productivity ones. The exact predictive margins of default are reported in Table 7.

FIGURE 2: Survival model regression results



Notes: This plot presents the differences between the predictive margins of liquidation of low productivity firms versus high productivity firms at any given rating $i \in A, B, C$

TABLE 7: Predictive Margins of Default

Firm Quality	Rating	Margin of Default
High	A	0.14%
Low	A	0.35%
High	B	0.84%
Low	B	1.22%
High	C	3.42%
Low	C	5.06%

Notes: Predictive Margins represent the marginal impact on the probability of default of being a low productivity or high productivity firm with a rating i

The other channel through which the reallocation effect can negatively affect aggregate productivity is by deterring entry. Unfortunately we cannot directly test this effect using firm level data, and in particular because we do not observe small firms in our dataset. However, these two channels (less entry and fewer exit of low productive firms) are not independent as the survival of low productive incumbents increase the cost of entry (see McGowan et al. 2017b,a).

These estimates however make an important assumption: we want the rating category to be independent from productivity levels and that the same share of low productive firms exists in each of our three categories. As explained before, productivity level and growth are not criteria that are directly considered in setting the Bank of France rating and any systematic difference would come from the correlation with another factor. Figure A1 in the Appendix shows that the distribution of productivity has the same shape in the three categories with a larger right-hand side tail for firms in rating category A. Importantly, the left-hand side tail is very similar across the three distributions which suggests that low productive firms exist in the three categories. In fact, 39% of the low productive firms have an A rating which means that they continue to have an relatively easy access to external financing although they are unproductive.

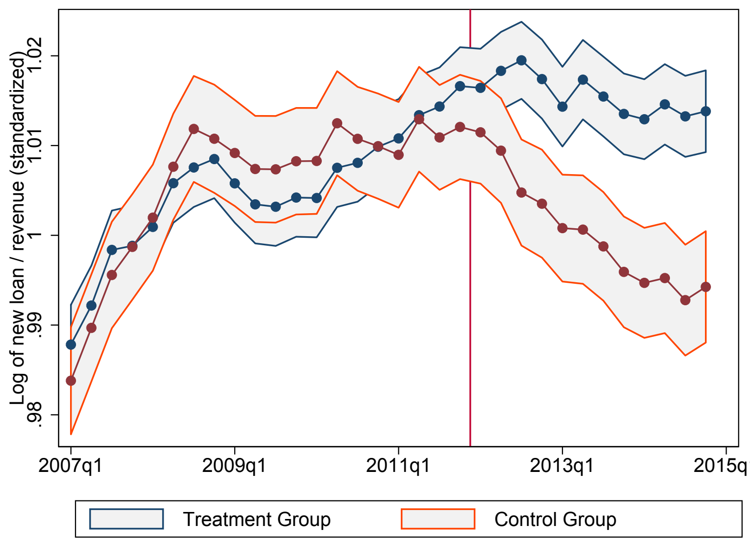
In the following section, we exploit an exogenous liquidity shock that affected some firms in the rating category B while leaving others unaffected to alleviate concerns about endogeneity problems in our two estimate results.

4.3 The Eurosystem's Additional Credit Claims program

Presentation

In the Euro Area, banks can pledge corporate loans as a collateral in their refinancing operation with the Eurosystem as long as these loans are considered to be of sufficient quality. Before 2012, loans to firms with a rating of 4^+ or better were eligible, which corresponds to our rating category A. In December 2011, the Eurosystem's Additional Credit Claims (ACC) program was announced and was implemented in February 2012. This program consisted of an extension of this eligibility framework to firms rated 4 (corresponding to part of our category B). It generated a discontinuity in credit access for firms that are rated 4 at the end of 2011. While many economic policy measures in the Euro Area were implemented at the same time, the ACC program is the only one that has generated a difference within firms in the rating category B (i.e. rated 4 or 5^+) between those treated by the program (rated 4) and which, from this, will benefit from the same eligibility advantage as firms with a higher rating, and the remaining firms of our category B that are not treated by this program (see Cahn et al., 2017 and Mesonnier et al., 2017 for recent studies using the ACC as a quasi-natural experiment).

FIGURE 3: New credits and ACC program



Notes: Treatment group corresponds to firms with a rating 4 in 2011, control group contains firm with a rating 5^+ in 2011. Log of the quantity of new credit divided by revenue has been standardized so has to be equal to 1 on average between 2007 and 2008. 95% confident interval are reported.

We consider the ACC as an event that exogenously reduced financial constraints for firms rated 4 at the end of 2011, which we compare with firms rated 5^+ in a regression discontinuity design.[10] Going back to our A-B-C classification, this means that after 2011, some firms in category B (those with a 4 rating) got closer to firms in category A. To show that this quasi-natural experiment indeed impacted the supply of new credit to firms, we report the average value of the quantity of new loans for the two categories of firms in Figure 3. What Figure 3 clearly shows is that prior to the ACC, the evolution of the value of new loans were not significantly different for firms rated 4 and 5^+ in 2011. The trends became significantly different only shortly after the program was set.

In the light of our model and our previous empirical results, we expect the ACC to have the following effects:

- Increase the productivity of firms with a 4 rating compared to similar firms with a 5^+ rating.

[10] Contrary to Mesonnier et al. (2017), we compare firms rated 4 with the control group of firms that had a rating immediately below (rating 5^+) and are therefore unaffected by the treatment. This is because, as argued by Cahn et al. (2017), the ACC also had positive effects on firms whose loans were already eligible to be pledged as collateral.

- Decrease the likelihood of exiting from liquidation for those treated firms, in particular if they have a low productivity.

Effect on TFP

We start by considering the effect of this shock on TFP. In our previous similar analysis reported in Table 3, we considered all firms and used the log of TFP in level as our dependent variable in the baseline model. This is because we were interested in the long run variation of productivity at different rating category. In this case, we restrict attention to the only two groups of firms that are very close and both in the rating category B. For this reason, and because we only observe three points following the ACC program (2012, 2013 and 2014), we consider as a dependent variable the growth rate of TFP. We therefore start by estimating the following model:

$$g_{i,t} = \beta_1 (Treated_i \times (postACC)_t) + X_{i,t}\gamma + \nu_i + \nu_{s,t} + \varepsilon_{i,t}, \tag{15}$$

where $g_{i,t}$ is TFP growth at t, $Treated_i$ is the dummy variable equal to 1 for firms that were rated 4 at the end of 2011, $(postACC)_t$ is a dummy variable equal to 1 from the year of the ACC program onwards, $X_{i,t}$ a vector of observed characteristics. Finally $\nu_{s,t}$ is a sector×year fixed effect and ν_i is a firm fixed effect, which is collinear to the dummy $Treated_i$. The first 3 columns of Table 8 show results of the estimation for our treated group (the firms that are rated 4 in 2011) and for a control group of firms rated 5^+ in 2011. Column 1 uses all manufacturing sectors while columns 2 and 3 restrict to sectors that are above (resp. below) the median in terms of financial dependence. As expected, the estimate of β_1 from equation (15) is positive and significant in column 1, and this is primarily driven by more financially dependent sectors. Then, in other columns, we show support that our effect is indeed due to the ACC program shock: columns 4 and 5 replace the variable (post ACC) by a dummy for t being larger than respectively 2006 and 2010 (and accordingly, define the treatment and control group based on their rating in 2005 and 2009), columns 6 and 7 consider two alternative of these treatment and control groups (respectively 3 and 4^+ and 5^+ and 5). All these placebo tests imply no significant response of our variable of interest.

TABLE 8: ACC PROGRAM AND PRODUCTIVITY SHOCK

Dependent variable	TFP growth						
	(1) **All**	**(2)** **RZ, high**	**(3)** **RZ, low**	**(4)**	**(5)**	**(6)** **All**	**(7)**
Treated×(post ACC)	1.066***	1.277**	0.750	0.518	0.136	0.415	-0.355
	(0.402)	(0.519)	(0.637)	(0.509)	(0.601)	(0.351)	(0.596)
$Log\,(L_{t-1})$	3.728***	2.009***	6.448***	3.882***	3.764***	4.085***	2.928***
	(0.369)	(0.446)	(0.653)	(0.493)	(0.403)	(0.393)	(0.518)
Fixed Effects	i + $s \times t$	i + $s \times t$	i + $s \times t$	i + $s \times t$	i + $s \times t$	i + $s \times t$	i + $s \times t$
R^2	0.141	0.139	0.144	0.160	0.143	0.134	0.156
Observations	86,885	54,434	32,451	45,524	72,558	83,540	45,413

Notes: TFP growth is given in percentage. Columns 1 and 2 test our hypothesis while columns 3 to 7 act as placebos. Columns 4 and 5 replace the variable (post ACC) by a dummy for t being larger than respectively 2006 and 2010, columns 6 and 7 consider two different groups of rating (respectively 3 and 4^+ and 5^+ and 5). All regressions have individual, rating trend and year×sector fixed effects. Firm clustered standard errors are reported in parentheses.

Effect on exit

Just like Table 8 shows results for the same kind of model as in Table 5, we now use our liquidity shock to run the same kind of model as the one presented in Table A2. More specifically, we estimate the following equation:

$$E_{i,t} = \beta_1(Treated_i \times (postACC)_t) + \beta_2 Treated_i + X_{i,t-1}\gamma + \nu_{s,t} + \varepsilon_{i,t}. \tag{16}$$

Here again, we do not use a fixed-effect estimator and estimate the model linearly using a simple OLS and a full set of sector-year fixed effects. For the sake of clarity, we do not use an interactor with the level of productivity of the firm B_i as we did in Table 6, but we run the model separately: first for all firms (columns 1 and 2 of Table 9), and then for low (resp high) productive firms (columns 3 and 4 of Table 9). Note that this time B_i is defined as the productivity level in 2011, just before the ACC shock. The reason is that we already impose that the firm is in the dataset in 2011 in order to allocate it to one of the two groups (treatment or control). Measuring the level of productivity in a year that is too far away in the past would impose that these firms are in the dataset for a long period and that they have survived for all this time. This would reduce and bias the sample significantly, especially for low productive and credit constrained firms.

We see that the coefficient of interested (i.e. β_1 in equation (16)) is negative and significant but only for low productive firms, which is in line with the cleansing mechanism that we highlighted in the model and in the previous regressions. These results show that a set of

TABLE 9: ACC PROGRAM AND RISK OF DEFAULT

Dependent variable	Default					
	All	**All**	**Low Prod.**	**High Prod.**	**Low Prod. High RZ**	**Low Prod. Low RZ**
(Rating = 4)	-0.011***	-0.010***	-0.013***	-0.009***	-0.013***	-0.013**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)	(0.005)
(Rating = 4)×(post ACC)	-0.007***	-0.006**	-0.012**	-0.004	-0.015**	-0.008
	(0.002)	(0.002)	(0.005)	(0.003)	(0.007)	(0.007)
Low Prod.		0.016***				
		(0.001)				
Fixed Effects	$s \times t$	$s \times t$	$s \times t$	$s \times t$	$s \times t$	$s \times t$
R^2	0.009	0.011	0.016	0.010	0.011	0.023
Observations	86,025	86,025	26,376	59,644	16,455	9,901

Notes: Quantiles are calculated according to the individual TFP in 2011. All regressions have individual and year×sector fixed effects. Regressions 3 to 7 also have a quantile×year fixed effect. Firm clustered standard errors are reported in parentheses.

low productive firms that had the right rating at the right time and that were subsequently positively hit by a credit shock are less likely to exit than otherwise similar low productive firms.

Finally, and to give more support to our story, we run the same model as the one presented in column 3 of Table 9 but separately for sectors with high (resp. low) RZ indicator. As expected, our results are mostly driven by the high-RZ sectors.

5 Conclusion

The literature on the relationship between access to credit and productivity has highlighted several channels of impacts, among which some possibly opposite. One is a positive impact of access to credit on productivity through the easier financing of productivity-enhancing investments. Another is a negative impact through capital misallocation, as evidenced in particular in Southern Europe during the 2000s.

We reconcile these different channels by putting forward an inverted-U relationship between access to credit and productivity growth. Two separate effects are simultaneously at play, a cleansing effect, dominating when access to credit is easy, and a productivity-enhancing investment financing effect, dominating when access to credit is tight. When access to credit is easy, restraining this access tends to increase aggregate productivity growth through dominant cleansing and creative destruction mechanisms: low-productivity incumbent firms will exit and free resources for entrants. However, beyond a certain level of constraint to credit access, these cleansing and creative destruction mechanisms are dominated by the fact that restraining further this access deteriorates the financing of productivity-enhancing investments, leading to a decrease in productivity growth.

We emphasize this relationship both theoretically and on French firm-level data. In the first part of this paper, we extend the model of innovation-led growth and firm dynamics by introducing credit constraints into the model. The model predicts that lower credit constraints (i.e. higher financial development) can have two opposite effects on aggregate innovation and growth. On the one hand, this helps good innovators to fully invest in innovation, which is good for aggregate innovation and growth. On the other hand, lower credit constraints make it easier for less efficient incumbent firms to remain on the market which, in turn, may discourage the entry and expansion of more efficient innovators, and thereby affect aggregate innovation and growth negatively. We show that these two counteracting effects of financial development result in financial development having an overall concave effect on aggregate innovation and growth, and that under reasonable assumptions the effect of financial development on innovation-led growth is an inverted U.

In a second part of the paper, we confront this model to French manufacturing firm level data. First, we study the correlation between credit availability and productivity growth. At the sector level, an inverted U relationship between credit spreads and access to credit appears for the sectors that are relying the most on external finance. At the firm-level, we decompose the inverted-U into its two channels: a positive impact on productivity growth of easier access to credit and a negative impact on the survival of the least productive firms, as evidence of the cleansing mechanism. We test these relationships with credit rating as a proxy for constraints on access to bank financing. Indeed, Banque de France credit rating may lead to credit constraints for badly rated firms as it is available to all banks, widely consulted and determines the eligibility of credit to the Eurosystem refinancing. Estimates using as a quasi-natural experiment, the 2012 change in the eligibility rating criteria of credit as collateral to Eurosystem refinancing, give a strong confirmation of our previous results. Lower credit constraints increase productivity of incumbent firms, this effect being higher for firms in sectors highly dependent on external finance than for those weakly dependent, and it reduces the firm default rate, this effects being higher for low productivity firms than for high productivity ones.

This relationship is related to the debate on secular stagnation. The decline in productivity growth in most advanced countries since the 1970s may be partly related to an overall easier access to credit due to financial liberalization over the period. This mechanism may have been amplified by the decrease of interest rates and the capital abundance observed the last decade. The increase of real interest rate expected in the recovery phase could contribute to increase productivity gains from more cleansing mechanisms. Hence, it would be particularly interesting to test this relationship over a longer time-period, which would require using macroeconomic data, in order to study the role of financial development on the long-term productivity deceleration observed since the 1970s.

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A Additional results

TABLE A1: Descriptive Statistics for the Manufacturing Sectors

Industry	Firms	L	Age	r	Entry	Exit	CD
Food	7,323	19	18	3.25	11.84%	9.97%	10.91%
Beverage	788	12	25	3.34	5.77%	6.85%	6.31%
Textile	1,364	20	21	3.40	6.66%	11.57%	9.11%
Apparel	1,507	16	19	3.38	13.97%	22.68%	18.33%
Leather and Shoe	463	29	21	3.44	6.74%	10.66%	8.70%
Wood	2,686	15	21	3.19	8.59%	10.73%	9.66%
Paper and Pulp	1,056	27	22	3.23	5.87%	9.32%	7.59%
Printing	2,978	16	21	3.45	7.87%	13.58%	10.73%
Chemical	1,818	27	20	3.19	6.46%	9.32%	7.89%
Pharmaceutical	421	76	21	3.11	6.99%	9.49%	8.24%
Rubber and Plastic	3,079	24	19	3.32	5.94%	8.96%	7.45%
Non-metallic Products	2,364	17	21	3.38	6.54%	8.45%	7.49%
Metallurgy	763	35	19	3.28	6.67%	8.90%	7.78%
Metallic Products	9,974	17	20	3.27	7.07%	8.31%	7.69%
Computer Products	1,686	22	18	3.57	8.55%	13.76%	11.16%
Electronic Equipment	1,431	25	19	3.36	8.08%	11.51%	9.79%
Machinery and Equipment	3,808	20	19	3.15	7.34%	11.20%	9.27%
Automotive	1,192	29	20	3.34	6.18%	8.84%	7.51%
Other Transportation Equipment	367	38	15	3.25	11.19%	12.41%	11.80%
Furniture	1,630	18	19	3.14	7.20%	12.69%	9.94%
Other Manufacturing	1,892	18	21	3.64	9.60%	11.46%	10.53%
Repair of Machinery	6,195	16	18	3.32	11.04%	12.93%	11.99%

Notes:This table reports the median level of (L) employment, age, real effective interest rate of new credits (r) and Entry rate, exit rate and creative destruction rate (CD) for private manufacturing firms with annual sales exceeding 750,000 euros or with outstanding credit exceeding 380,000 euros from the years 2004 to 2014. The data has been trimmed for the top and bottom 1% of TFP growth values. The information for employment and age is obtained from *Fiben*'s firm-level database while that for effective interest rates is obtained from *MContran*'s random sample of new investment loans which has been trimmed for the top and bottom 1% of interest rate values. Entry (Exit) rate is defined as the number (in %) of new (exiting) firms at t relative to the stock of firms at t-1 and creative destruction, defined as the average of the entry and exit rates. These data are taken from the *INSEE's* SIRENE database. The tobacco and the processing and coking industries are dropped throughout because of the little amount of firms in those sectors.

FIGURE A1: TFP distribution for each rating category

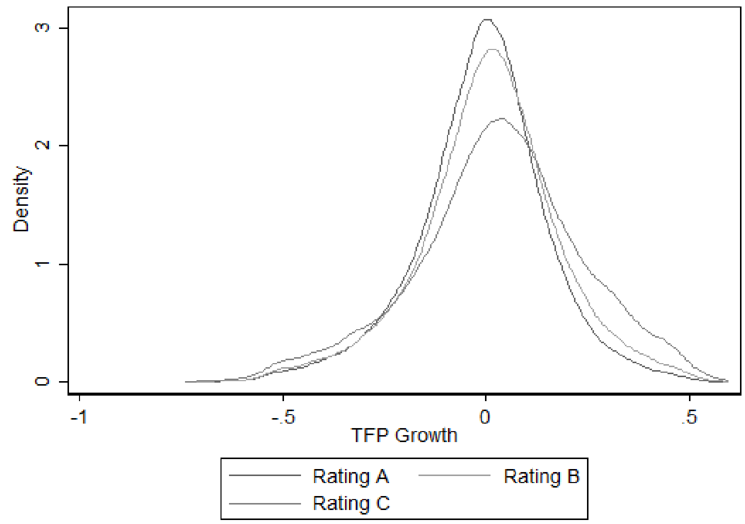

TABLE A2: LIQUIDATION AND RATING

Dependent variable	Liquidation at $t+2$ dummy				
	(1)	**(2)** All	**(3)**	**(4)** High RZ	**(5)** Low RZ
Rating Category					
A	-0.019***	-0.018***	-0.018***	-0.021***	-0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
C	0.057***	0.056***	0.051***	0.050***	0.052***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
$Log(L_{t-1})$	-0.003***	-0.002***	-0.002***	-0.003***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.000***	-0.000***	-0.000***	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Low Prod.		0.008***			
		(0.001)			
Rat. Cat. A $\times$ Low Prod			0.004***	0.005***	0.003**
			(0.001)	(0.001)	(0.001)
Rat. Cat. B $\times$ Low Prod			0.006***	0.004*	0.008***
			(0.002)	(0.002)	(0.002)
Rat. Cat. C $\times$ Low Prod			0.020***	0.024***	0.015***
			(0.004)	(0.005)	(0.006)
Fixed Effects	$s \times t$	$s \times t$	$s \times t$	$s \times t$	$s \times t$
R^2	0.036	0.036	0.037	0.036	0.039
Observations	188,636	188,636	188,636	120,465	67,982

Notes: This table show result of a similar regression as the one displayed in Table 6 but defining a low productivity firm as a firm with a productivity level among the 25% lowest of its sector in 2004.