# The Inverted-U Relationship Between Credit Access and Productivity Growth*

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**Abstract**

In this paper we identify two counteracting effects of credit access on productivity growth: on the one hand, better access to credit makes it easier for entrepreneurs to innovate; on the other hand, better credit access allows less efficient incumbent firms to remain longer on the market, thereby discouraging entry of new and potentially more efficient innovators. We first develop a simple model of firm dynamics and innovation-base growth with credit constraints, where the above two counteracting effects generate an inverted-U relationship between credit access and productivity growth. Then we test our theory on a comprehensive French manufacturing firm-level dataset. We first show evidence of an inverted-U relationship between credit constraints and productivity growth when we aggregate our data at sectoral level.. We then move to firm-level analysis, and show that incumbent firms with easier access to credit experience higher productivity growth, but that they also experienced lower exit rates, particularly the least productive firms among them. To confirm our results, we exploit the 2012 Eurosystem's Additional Credit Claims (ACC) program as a quasi-experiment that generated exogenous extra supply of credits for a subset of incumbent firms.

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# 1 Introduction

The existing literature on finance and growth since the 1990s argues that lower financial constraints - or better credit access - should have an unambiguously positive effect on economic growth and especially on innovation-based growth (in particular, see King and Levine 1993, Levine 1997 and Rajan and Zingales 1998). In this paper we identify two counteracting effects of credit access on productivity growth. One the one hand, better access to credit makes it easier for entrepreneurs to innovate, this is the direct effect already emphasized by the existing literature on financial development and innovation-based growth. On the other hand, there is an indirect *reallocation* effect of credit access on productivity growth: namely, better credit access allows less efficient incumbent firms to remain longer on the market, thereby discouraging entry of new and potentially more efficient innovators. This latter counteracting effect is quite similar to the negative reallocation effect of subsidizing incumbent firms in Acemoglu et al. (2018).

In the first part of the paper, we develop a simple model of firm dynamics and innovation-base growth with credit constraints, to formally uncover the direct and indirect effects of credit access on productivity growth. Moreover, the model shows that, under suitable conditions, these two counteracting effects generate an inverted-U relationship between credit access to incumbent firms and productivity growth.

In the second part of the paper we confront our theoretical predictions to the data. We use the FiBEn firm-level database constructed by the Bank of 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 rating variable called "Cotation" which rates firms according to their financial strength and capacity to meet their financial commitments. This "Cotation" (or rating) measure is considered to be a proxy for credit access, as it is widely used by banks when deciding whether and how much to grant credit to firms, and it is also used by the Eurosystem - in particular the European Central Bank (ECB) - when assessing whether a bank's credit to a particular firm can be pledged as collateral against central bank refinancing, and we indeed show that this rating measure is indeed positively correlated with the firm's credit access (measured by both, the amount of loans the firm gets and the interest rate it faces).

We first perform cross-sector panel analysis. There, we regress sectoral growth on a sectoral measure of credit constraint - namely the difference between the average rate of new loans to firms in the sector and a reference rate, controlling for sector fixed effects. We find evidence on an inverted-U relationship between credit constraints and productivity growth.

We then move to firm-level analysis. We first run OLS regressions on the productivity growth and exit rates of incumbent firms on the *Cotation* measure of credit constraint. We find that incumbent firms with easier access to credit (i.e. with higher rating measure) experience higher productivity growth, but we also find that incumbent firms with easier credit access experience lower exit rates, particularly the least productive firms. This we see as primary evidence we find evidence of both, the direct *investment* effect and the indirect *reallocation* effect of improved credit access. To reinforce our results and deal with potential endogeneity issues, we exploit a policy change which improved credit access for only a subset of incumbent firms as of a specific time. Namely, we use the 2012 Eurosystem's Additional Credit Claims (ACC) program, which extended the set of loans eligible for banks' refinancing with the ECB. As mentioned above, in the Euro Area banks can pledge corporate loans as collateral in their refinancing operations with the ECB as long as these loans are of sufficient quality, i.e. as long as the corresponding firms' ratings are sufficiently good. What the ACC program did was to extend the eligibility criterion to include a specific group of French firms (those rated 4 in Bank of France's rating system) from February 2012 onwards.[1] We show that incumbent firms directly affected by this ACC program experienced an upward jump in productivity growth post-ACC, but we also show that these treated firms experienced lower exit rates, and particularly those treated firms that were the least productive before the introduction of ACC program.

Our analysis relates to several strands of literature. First, to the literature on financial development and growth. Here we refer the reader to the survey by Ross Levine in Levine (2005).[2] We depart from this literature by uncovering a negative "reallocation" effect of credit access to incumbent firms, and by showing that the combination between the positive direct effect of credit access emphasized in the literature and this negative reallocation effect, can give

[1]For more information on the ACC program, see Mesonnier et al. (2017) and Cahn et al. (2017).

[2]The direct effect of credit access on R&D investment and innovation is shown by Aghion et al. (2012) on a large dataset of French firm (see also 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 similar results. For instance, Duval et al. (2017), Besley et al. (2018) and Manaresi and Pierri (2017), respectively on US, UK and Italian firms show that higher financial constraints have a detrimental impact on productivity growth around the time of the crisis. They highlight a similar channel, namely that firms which are exposed to financial constraints lower their investments, especially in assets with a strong impact on productivity, such as R&D, ICT or intangible capital.

rise to an inverted-U relationship between credit access and productivity growth.

Second, our paper relates to the literature on firm dynamics and growth. Here, primary references are Klette and Kortum (2004), Akcigit and Kerr (2010, 2018), and Acemoglu et al. (2018), and we also refer the reader to Aghion et al. (2015) for a simple presentation of the basic framework and of the ideas developed by this literature. We contribute to this literature by introducing credit constraints into the framework, showing that easier credit access for incumbent firms has the same counteracting effects on productivity growth as the subsidies analyzed by Acemoglu et al. (2018), and that the overall effect of credit access on productivity growth can be an inverted-U.

Third, a recent empirical literature has argued that the low real interest rates and financial constraints already before the financial crisis, might partly explain the productivity slowdown, i.e. the decrease in productivity growth, experienced in the US and other developed countries over the past period. Thus Gopinath et al. (2017) show that the marginal product of capital has become more dispersed in southern Europe within the manufacturing sector.[3] In the same vein, using data from 260 US metropolitan statistical areas (MSA) over the 2007-2014 period, Gropp et al. (2017) show that higher financial constraints enhance cleansing mechanisms and in particular job destruction with a positive impact on MSA-level average productivity growth. In line with our *reallocation* effect, this literature already suggests that due to lower financial constraints and real interest rates, high-productivity firms increasingly failed to crowd out the least efficient ones.[4] We contribute to this literature by developing a model of credit access, firm dynamics and growth, and by showing that, in line with the model's prediction, the positive direct *investment* effect and the negative *reallocation* effect can result in an overall inverted-U effect of credit access on productivity growth, In other words, a decrease of credit constraints reduces the cleansing mechanisms.

The paper is organized as follows. Section 2 presents motivating cross-sector panel evidence of an inverted-U relationship between credit constraints and productivity growth. Section 3 develops a model of the two main counteracting effects of credit access on productivity growth, which generates the inverted-U. Section 4 presents our data and some main empirical facts. Section 5 presents our empirical strategy and main empirical results. Section 6 concludes.

[3] See also Reis (2013) and Cette et al. (2016) for consistent findings.

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

# 2 Sectoral evidence of an inverted-U

To motivate our analysis in the remaining part of the paper, here we present some first evidence of an inverted-U relationship between credit constraints (or credit access) and productivity growth at sectoral level. For each year and each 22 two-digit manufacturing sector, we calculate the difference between the average rate of new credits[5] to the sector and a reference rate, which we choose to be the average yearly value of the Euro OverNight Index Average ($EONIA$)[6]. We refer to this difference as the "Spread" variable in what follows. Then we estimate the tightness of credit constraint in the sector in a given year by looking at how the spread measure that year deviates from its time average. This spread indeed reflects banks' credit risk assessment of the sector in any particular year, and hence their willingness to grant credit to firms in this sector that year. We thus estimate the equation:

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

where $g_{s,t}$ is the sector's current TFP growth and $\nu_s$ is a sector fixed effect. Estimates presented in the first column of Table 1 show that, as expected, $\beta_1$ is positive and $\beta_2$ negative. These findings suggest an inverted-U relationship between credit access and productivity growth, which in turn we try to rationalize in the next section.

Next, we split sectors into those that are above versus below the median in terms of their external financial dependence (see Rajan and Zingales 1998). We consider two indicators to measure a sector's level of external financial dependence (or EFDI): (i) the Rajan and Zingales (1998) indicator, computed as the ratio of externally financed capital expenditure over total capital expenditure for manufacturing firms in the corresponding US sector, where the former is taken to be equal to the difference between total capital expenditure and cash flow from operations. It is denoted as "RZ" throughout the paper; (ii) a second indicator following Aghion et al. (2017), equal to the labor cost to sales ratio for US firms in the corresponding manufacturing sector, which in turn we compute using the NBER-CES manufacturing industry database. It is denoted as "US" throughout the paper. In both cases, the inverted-U relation-

[5]Data on new credits come from the $MCONTRAN$ database. Similarly, we aggregate firm-level TFP growth calculated from $FiBEn$ at the sectoral level to measure sectoral productivity growth. All these data will be presented below, see section 4

[6]This is the rate at which banks lend to each other on a short-term basis. Daily and average yearly rates of the EONIA from 2000 to 2017 are plotted in the Appendix, Figure A2.

ship between the spread and productivity growth turns out to be significant only for sectors with US counterparts displaying high external financial dependence ratios.

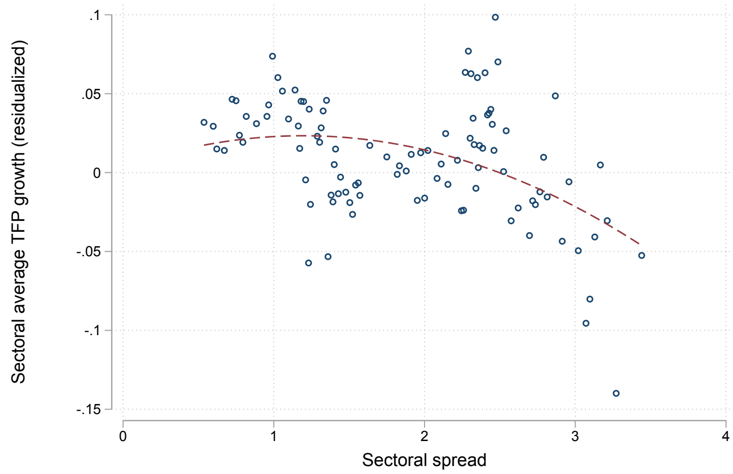
Table 1: Sectoral interest rate and productivity

| Dependent Variable | Sectoral TFP growth (in %) | | | | |
|---|---|---|---|---|---|
| Dependence Indicator (EFDI) | All | RZ, high | RZ, low | US, high | US, low |
| Spread | 3.375 | 3.606 | 2.972 | 3.346 | 3.379 |
| | (2.072) | (2.853) | (3.152) | (2.700) | (3.135) |
| Spread Squared | -1.401** | -1.616** | -1.107 | -1.470** | -1.327 |
| | (0.571) | (0.772) | (0.889) | (0.717) | (0.888) |
| Fixed Effects | Sector | Sector | Sector | Sector | Sector |
| $R^2$ | 0.278 | 0.396 | 0.116 | 0.363 | 0.173 |
| Observations | 242 | 132 | 110 | 121 | 121 |

**Notes**: The dependent and independent variables are calculated as means per sector and year. All regressions include sector fixed effects. Heteroskedasticity robust standard errors, clustered at the sector level are reported in parentheses. Time period: 2006-2016.

Figure 1 plots the average TFP growth in that sector and year against the corresponding value of the "spread" variable for each sector associated with an RZ value of 1 and each year. In this figure we have residualized the spread on a sector fixed effect so we essentially consider deviations from the sectoral mean of its value. The quadratic fit line is also shown and echoes our findings in Table 1.

Figure 1: Sectoral spread and TFP growth




**Note:** Each dot represents a sector in a specific year from 2006 to 2016. 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.

# 3 A toy model of firm dynamics and growth with credit constraints

In this section we develop a simple variant of Klette and Kortum (2004)'s model of firm dynamics and productivity growth with credit constraints, which generates an inverted-U relationship between credit access and productivity growth in line with our preliminary evidence in the previous section. We closely follow the presentation of Klette-Kortum in Aghion et al. (2015) but then adding credit constraints to the framework. In the Klette-Kortum model and its subsequent extensions, including the one we develop below: (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.

## 3.1 The setup

Time is continuous and a continuous measure $L$ of individuals decide to work either as production workers or as researchers in incumbent firms or in potential entrants. We assume a logarithmic intertemporal utility function for the representative consumer:

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

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

The final consumption good is produced competitively using a continuum of intermediate goods according to:

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

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 $j$. That innovator uses labor according to the linear technology:

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

where $A_{jt}$ is the labor productivity on product line $j$ at time $t$, and $l_{jt}$ is the labor employed by that product line for producing its intermediate input. Hence the marginal cost of production in $j$ is equal to $w_t / A_{jt}$ where $w_t$ is the wage rate in the economy at time $t$.

A firm is defined as a collection of $n$ product lines. Firms expand in the product space through successfully innovating on other lines. We assume the following innovation technology: an $n-$- product firm employing $S_i$ researchers innovates at Poisson flow rate

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

where $\frac{1}{\eta}$ is the elasticity of innovation with respect to scientists and $\zeta$ 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 the firm successfully innovates, it improves productivity by factor $\gamma > 1$ on some product line other than those it was already operating in. This in turn allows the firm to expand the number of its production lines from $n$ to $n+1$. At the same time, on each of its $n$ current production lines the firm faces the flow probability $x$ that productivity will be improved upon by another firm (incumbent or entrant). Whenever that happens the size of the firm will shrink from $n$ to $n-1$, and if the firm was operating on one line only to begin with (i.e. if $n=1$), then the firm simply exits the market. Overall, during any small time interval $dt$, firm size increases to $n+1$ with probability $Z_i dt$ and decreases to $n-1$ with probability $nxdt$,and a firm that loses all of its product lines exits the market.

Finally, we assume that a potential entrant innovates upon an existing line by factor $\gamma$ by hiring $\psi$ scientists, and that there is free-entry so that in equilibrium the firm the discounted value of becoming a one-product firm is equal to the research labor cost $\psi w_t$.

## 3.2 The model without credit constraints

Here we simply reproduce Klette and Kortum's analysis as presented by Aghion et al. (2015). The analysis proceeds in two steps: first, one solves for the static production decision and second one solves for innovation decision of firms, which then determine the equilibrium rate of productivity growth.

### 3.2.1 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 $j$. Consequently, 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 of potential producers endowed with the previous technology on this 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

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

### 3.2.2 Dynamic innovation decision

Let $V_t(n)$ denote the 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 straightforward to show (see Aghion et al. 2015 ) 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 $v$ satisfies:

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

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 $\omega$.

#### 3.2.3 Entrants

A potential entrant innovates upon an existing line by factor $\gamma$ by hiring $\psi$ scientists. Free-entry implies that the value of a new entry $V_t(1)$ must be equal to the innovation cost $\psi w_t$, so that:

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

If now one denotes the entry rate per existing line by $z_e$, and uses the fact that the overall rate of creative destruction on each existing line is equal to the sum of entry rate on that line plus the rate of creative destruction by an incumbent firm, we get:

$$x = z_i + z_e.$$

This, together with (5), (6) and (7), yields (see Aghion et al. 2015):

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

#### 3.2.4 Labor market clearing

As shown in Aghion et al. (2015), the Klette-Kortum 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 $\zeta z_i^{\eta}$ of scientists by incumbent firms; (iii) the third term is the aggregate employment $\psi z_e$ of scientists by entrants.

This equation yields:

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

#### 3.2.5 Equilibrium growth rate

Innovation occurs on each line at a flow rate equal to $x = z_i + z_e$. And we know that whenever an innovation occurs on a product line labor productivity on that line is multiplied by $\gamma$.

This yields the following expression for the equilibrium growth rate in the absence of credit constraints (see Aghion et al. 2015 ):

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

## 3.3 Introducing credit constraints

Our focus in the empirical analysis, will be on the effect of easing credit access on a subgroup of *incumbent* firms. Hence our focus in this section on the case where credit constraints are binding for incumbent firms only. As it turns out, in the case where credit constraints are binding on the potential entrants only, credit easing only has a positive direct effect on innovation-based growth, the negative *reallocation* effect disappears and with it the possibility of an inverted-U relationship between credit access and growth.

We model credit market imperfections by assuming that intermediate firms cannot invest more than $\mu$ 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

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

As mentioned above, we shall focus on the case where potential entrants have accumulated enough wealth for the credit constraint not to be binding on them. [7]

[7] That 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:

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

We shall, however, focus on the case where (9) is binding as the first case is studied in the previous analysis. 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 $\mu$ has two counteracting effects on $g$ : on the one hand a higher $\mu$, i.e less credit constraints, increase innovation intensity by incumbents, this is the second term on the RHS of (10): this corresponds to a positive *investment effect* of relaxing credit constraints; on the other hand, a higher $\mu$ 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 $\mu$ and $g$, but not an inverted-U. However, it is straightforward to extend the model so as to obtain an inverted-U relationship between $\mu$ and $g$. Thus if the innovation size $\gamma_e$ for entrants is strictly larger than the innovation size $\gamma_i$ for incumbents, then the equilibrium growth rate $g$, equal to

$$g = (\frac{\pi}{\omega\psi} - \mu - \rho)\ln\gamma_e + \left(\frac{\mu\psi}{\zeta}\right)^{1/2}\ln\gamma_i \tag{11}$$

satisfies:

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

where $\mu = \frac{\psi}{4\zeta}$ is the maximum value of $\mu$ for which the credit constraint is binding.[8]

### 3.4 Summary

The model in this section generated two counteracting effects of credit access on productivity growth: a direct positive *investment* effect whereby easier credit access allows incumbent firms to invest more in innovation-led growth; and an indirect negative *reallocation* effect whereby easier credit access reduces increases the entry cost of new potentially more efficient innovators. And we showed that under suitable conditions the combination of these two effects could result in an inverted-U relationship between credit access and productivity growth in the aggregate. In the next section we provide firm-level evidence of the investment and reallocation effects.

## 4 Data and facts

### 4.1 Firm-level Data

Our main source of data is FiBEn. FiBEn is a large French firm-level database constructed by the Bank of France based on fiscal documents, and which includes balance sheet and P&L statements, and contains detailed information on firms' activities and firms' size. FiBEn in-

[8]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.

cludes all 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 onwards and is complete up to 2016. We shall however restrict attention to the subperiod 2004-2016 due to availability limits for other data. We shall also restrict the sample to private manufacturing firms for which we can measure productivity most accurately.[9] Table 2 shows the median values for key variables (total employment, value added, age and TFP growth)[10] for our dataset starting in 2004.[11]

Table 2: Descriptive Statistics for Firms in the Manufacturing Sector

| **Year** | **L** | **Y** | **Age** | **g** | **Firms** |
|---|---|---|---|---|---|
| 2004 | 18 | 843 | 16 | 4.71 | 19,315 |
| 2005 | 18 | 860 | 16 | 3.10 | 19,896 |
| 2006 | 18 | 908 | 17 | 4.70 | 20,519 |
| 2007 | 19 | 959 | 17 | 2.20 | 22,311 |
| 2008 | 19 | 992 | 18 | 1.24 | 23,843 |
| 2009 | 20 | 1,021 | 20 | -2.28 | 27,670 |
| 2010 | 19 | 1,048 | 21 | 4.09 | 28,014 |
| 2011 | 19 | 1,072 | 21 | 3.38 | 28,153 |
| 2012 | 19 | 1,073 | 22 | 0.01 | 28,085 |
| 2013 | 19 | 1,080 | 23 | 0.08 | 27,489 |
| 2014 | 19 | 1,082 | 23 | 1.11 | 27,367 |
| 2015 | 19 | 1,061 | 24 | -1.15 | 27,042 |
| 2016 | 19 | 1,114 | 24 | 2.28 | 25,834 |

**Notes**: This table reports the median level of employment (L), real value added in thousand euros of 2014 (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 2016. TFP is calculated following Levinsohn and Petrin (2003). Source: *Fiben*.

## 4.2 Bank of France's rating of firms

In addition to firms' 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 these are available only from a small random sample of firms.

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

[10] While this Table shows yearly median values over all our sample, Table A1 in Appendix A gives sector level median of key variables.

[11] We note that the age of the median firm increases in time. The same would be true had we used the age of the average firm. This does not result from the treatments we do to our data but from the fact that relatively less manufacturing firms are created each year, at least on the set of firms that are present between 2004 and 2016. See Figure A1 in Appendix A.

For that reason, we shall mostly rely on a proxy to measure firms' credit access: namely, Bank of France's credit rating called "Cotation". "Cotation" is a rating index which classifies companies according to their financial strength and capacity to meet their financial commitments over a three-year horizon. A firm can be rated from $3^{++}$ to 9 (and P in case of collective insolvency proceedings), but we have grouped firms in three different categories for the sake of simplicity: category A, includes firms with rating level $3^{++}$ (those firms are deemed to display an outstanding ability to meet their financial commitments) and firms rated $4^{+}$ (firms with rather strong ability to meet their financial commitments); category B includes firms rated 4 (correct ability) and $5^{+}$(rather weak ability); and category C includes firms rated 5 (weak ability) and firms rated P (doomed to become insolvent). 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 system resorts to balance sheet based formula as rarely as possible with a strong preference for on-site visits and interviews. These ratings are 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 3 shows that firms in the best categories are larger, older and more productive than other firms. On average, firms rated in the worst category have about 8% chance to be liquidated in the near future. All these descriptive statistics are reported in Table 3.

Table 3: Descriptive Statistics for the Bank of France Rating

| **Cat.** | **L** | **Y** | **Age** | **TFP** | **Liquidation** | **Obs.** |
|---|---|---|---|---|---|---|
| A | 19 | 1,183 | 21 | 4.80 | 0.43 | 173,097 |
| B | 18 | 869 | 20 | 4.57 | 2.12 | 112,162 |
| C | 19 | 752 | 17 | 4.42 | 8.35 | 40,279 |
| Total | 19 | 1,010 | 20 | 4.68 | 1.99 | 325,538 |

**Notes**: This Table reports the median value of some variable for firms in different rating categories as described in section 4.2. L and Y stand 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 4.3

All private banks can access this rating information and use it when deciding whether and how to provide credit to firms. In addition, as we shall see below, this credit rating is used by the Eurosystem to set the threshold below which corporate loans are eligible for being pledged as collateral by banks in their refinancing operations with the Eurosystem.

This rating information is widely available to banks, largely consulted and largely correlated with credit volume and price. This in turn motivates us to use this rating as a proxy for credit access by incumbent firms.

Using our data on new loans, one can first check this relationship between the Bank of France's ratings and actual credit access by firms.[12] On average, as reported in the top panel of Table 4, firms that are in rating category A borrow at a rate of 2.8% and 2.9% respectively for short-term (with maturity below one year) and long-term loans, while firms in rating category C borrow at a rate of 3.4% and 3.6%. We further explore these correlations between rating category and the price/quantity of loans by running a linear model controlling for individual and sector characteristics. Results are shown in the bottom panel of Table 4 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 or long term loans. Differences between categories B and C are less clear in terms of quantities, but large and significant in terms of interest rates.

### 4.3 Liquidation

We complete our above datasets with information on all court-ordered liquidations (or winding-up) of firms which have defaulted at least once. Following a liquidation event, the firm almost always exits from the market and its assets are redistributed to the firms' claimants. We consider this as a reliable indicator of a firm exiting the market due to financial difficulties rather than exiting our data sample for some other reason (for example because the data producer would not have reported the firm's balance sheet or because the firm owner retired). The Bank of France keeps track of all previous legal events regarding liquidation procedures and we therefore cover comprehensively the winding-up of firms with the exact year the firm ceased to exist. While this dataset is a great valuable source of information regarding exit of firms, it suffers from one drawback. Indeed, when a firm is about to disappear due to financial difficulties, it is very likely that this firm will stop sending its balance sheet to the Bank of France a few years

[12]We select only a subset of all the loans that are available in *MCONTRAN* following the same procedure as Mesonnier et al. (2017). In particular, we restrict our sample to financial instruments and non-subsidized loans made by private banks. We are left with 7,540 observations for short term credits (maturity below one year) and 1,971 for long term credits.

before disappearing. This raises a technical difficulty in our data construction because it is then almost impossible to observe the balance sheet of the firm in the years before its liquidation from $FiBEn$. We then chose to create a binary variable that takes the value 1 the last year the firm appears in our database if it to be subsequently 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 for most of the cases it is equal to 2 years. In any case, even if we are able to retrieve balance sheet information that are less than two years before liquidation, we won't consider it.

Note that the Bank of France rating is a good indicator of liquidation risk. This is shown in Table 3 and described in more details in the annual evaluation of this rating (see Banque de France, 2017 for a recent vintage). Another way of seeing this is to consider all firms that are in the data in 2004. Among these firms, more than 30% that have a C rating in 2004 will be liquidated by 2016 with a peak during the crisis, against less than 10% for the best rated ones.

Table 4: Rating, interest rates and quantities borrowed

| Dependent variable | **r** | **r** | **log(Q)** | **log(Q)** |
|---|---|---|---|---|
| Maturity | Short Term | Long Term | Short Term | Long Term |
| **Panel A: Average values and standard deviations** | | | | |
| **Rating category** | | | | |
| A | 2.79 | 2.92 | 12.6 | 11.4 |
| | (1.40) | (1.34) | (1.12) | (1.33) |
| B | 2.85 | 3.01 | 12.2 | 11.0 |
| | (1.40) | (1.32) | (1.09) | (1.19) |
| C | 3.39 | 3.57 | 12.3 | 11.0 |
| | (1.47) | (1.50) | (1.04) | (1.19) |
| **Panel B: Linear regression results** | | | | |
| **Rating category** | | | | |
| A | -0.337*** | -0.322*** | 0.241*** | 0.352*** |
| | (0.017) | (0.028) | (0.044) | (0.064) |
| B (ref) | | | | |
| C | 0.305*** | 0.289*** | -0.042 | -0.004 |
| | (0.029) | (0.060) | (0.061) | (0.080) |
| $Log(L)$ | -0.082*** | -0.080*** | 0.689*** | 0.425*** |
| | (0.011) | (0.014) | (0.027) | (0.023) |
| Age | -0.002*** | -0.001 | 0.002** | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Fixed Effects | $s \times t$ | $s \times t$ | $s \times t$ | $s \times t$ |
| $R^2$ | 0.809 | 0.782 | 0.389 | 0.303 |
| Observations | 7531 | 1934 | 7531 | 1934 |

**Notes**: Panel A reports average values and standard deviation for the rate $r$ (in %) and log quantity $Q$ (in euros) for each of the three rating categories defined in the text. Panel B reports results from a pooled-OLS regression of these variable on a dummy for each rating category, controlling for the log of employment and age of the firm and adding a set of sector $\times$ year fixed effects. Estimates are obtained using an OLS estimator. Heteroskedastic robust standard error, clustered at the sector level are reported in parentheses. Columns 1 and 3 take information from short term loans (maturity $< 1$ year) while columns 2 and 4 only consider long term loans. Time period is 2006-2016 due to data availability on credit.

# 5 Firm-level Results

## 5.1 Empirical Strategy

Directly testing an inverted-U shape relationship between credit access and productivity growth using firm-level data raises at least two empirical difficulties. First, while the direct effect can be directly tested using our dataset, [13]the reallocation effect of credit access on productivity growth works through the effect that reduced exit of an incumbent firm has on other firms, namely the potential entrants into the sector. The resulting impact on productivity can only be seen at the aggregate level and all we can do is provide indirect evidence of reallocation effect by looking at the impact of improved credit access on the exit rates of incumbent firms. In particular we hope to find that better credit access reduces exit rates particularly for the least efficient incumbent firms.

Second, we need to deal with the issue of reversed causality from past firm productivity performance to current access to external finance. To address this issue, we exploit a quasi-experiment in Section 5.3. Namely, we use the ACC program - which extended the eligibility criterion for loans to be used as collateral for banks' refinancing operations with the ECB -, and then perform diff-in-diff regressions where we compare productivity growth and exit rates of firms before versus after the introduction of the ACC program in early 2012, respectively for firms that are directly concerned by the ACC program (firms with a rating 4, the treatment group) and firms that are not directly concerned by the program but with a rating immediately below (namely, firms with a rating $5^{+}$, the control group, within category B).

## 5.2 OLS analysis

In this subsection, we regress firm-level productivity growth on our rating indicator as a measure of credit constraints. We think that the correlation analysis performed in this subsection should not be disregarded, especially since the experts that set the firm's rating do not directly consider productivity and are mostly focused on the overall financial soundness of a firm resulting from its solvency, profitability, liquidity, etc... Similarly, banks put more weight on more direct information on the firm's performance such as its profitability and its current debt level (debt

[13]Conditional upon finding an exogenous measure of financial constraints that is not directly related to the firm's past performance (we come back to this issue below).

overhang). Yet, to the extent that financial ratios and profitability measures are not totally independent from productivity performances, the OLS results below cannot be considered as causal. Hence, in the next subsection, we shall exploit a regulatory discontinuity, namely the introduction of the ACC program, which generated an exogenous shift in credit access to a subset of incumbent firms, to address this endogeneity issue.

### 5.2.1 Firm-level productivity and productivity growth

Here we look at the direct effect of the rating category on the productivity of incumbent firms. By focusing on incumbent firms, we seek to isolate on the second term of equation (11) and to focus on the positive *investment effect* of relaxing credit constraint. We hence consider the following linear models:

$$tfp_{i,t} = \sum_k \alpha_k Cot_{i,t}^{(k)} + X_{i,t}\gamma + \nu_i + \nu_{s,t} + \varepsilon_{i,t}, \tag{12}$$

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, $\nu_i$ 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 $\alpha_k$ 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. Estimate results of this relation are presented in the first 3 columns of Table 5. Column 3 uses a full set of fixed effects $\nu_i$ and $\nu_{s,t}$ and shows that having the best rating is associated with a productivity level that is 8.6% larger than a firm in the same sector which has a rating category B.

In the next three columns of Table 5, we consider the growth rate of TFP as our dependent variable. Because firms 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.[14] This model is estimated with OLS, but using the Arellano-Bond GMM estimator delivers similar results. Our results are consistent with what was found in

[14] More specifically, we estimate the following model of $\beta$-convergence:

Table 5: Rating categories and TFP

| Dependent variable | Individual TFP (log) | | | Growth rate of TFP (in %) | | |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| **Rating Category** | | | | | | |
| A | 0.222*** | 0.084*** | 0.086*** | 2.349*** | 2.688*** | 3.493*** |
| | (0.003) | (0.002) | (0.002) | (0.097) | (0.142) | (0.138) |
| B (ref) | | | | | | |
| C | -0.154*** | -0.081*** | -0.079*** | 0.400** | -1.248*** | -2.088*** |
| | (0.003) | (0.002) | (0.002) | (0.167) | (0.224) | (0.218) |
| $log(L)$ | 0.242*** | 0.028*** | 0.024*** | 3.876*** | -2.879*** | -2.451*** |
| | (0.002) | (0.005) | (0.005) | (0.066) | (0.399) | (0.400) |
| Age | 0.001*** | 0.010*** | | -0.001 | 0.370*** | |
| | (0.000) | (0.000) | | (0.003) | (0.015) | |
| $log(TFP)_{t-1}$ | | | | -16.638*** | -59.924*** | -65.615*** |
| | | | | (0.195) | (0.361) | (0.369) |
| Fixed Effects | $s \times t$ | $i$ | $i + s \times t$ | $\times t$ | $i$ | $i + s \times t$ |
| $R^2$ | 0.485 | 0.843 | 0.860 | 0.107 | 0.361 | 0.403 |
| Observations | 325,482 | 319,712 | 319,712 | 308,193 | 303,030 | 303,030 |

**Notes**: This table shows results from an estimation of equation (12). The dependent variable is 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.

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 in other rating categories.

We interpret these results as reflecting a direct impact of credit access on productivity level and productivity dynamics. 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. To give support to this interpretation, we show in Appendix (Table A2) that our results are consistent if TFP is replaced by the investment rate (the ratio of investment over capital), suggesting that a lower rating is associated with less opportunities to invest.

One may worry that these results capture the fact that some firms are just poorly managed and consequently show both, a lower productivity and a lower propensity to meet their financial commitments. Then the rating indicator or any other measure of credit supply would be correlated with TFP but not so much because of an investment effect. Note that this concern

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

is at least partially alleviated by the introduction of a firm fixed effect which captures the time invariant idiosyncratic quality of a firm. We further deal with the existence of such confounding factors and other potential endogeneity issues in the next subsection 5.3.

### 5.2.2 Exit

To capture the negative reallocation effect of credit access, we look at the effect of credit access on the exit rates of more versus less productive firms.[15] Using our information on liquidations, we run the regression:

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

where: $E_{i,t}$ is a binary variable that takes the value 1 if the firm is about to be liquidated (see section 4.3); $X$ is a control vector which 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 date $t-1$.[16] 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 using one such method, let us first consider a linear model and estimate equation (13) using a simple OLS estimator.

Estimation results of model (13)'s parameters are reported in Table 6. The results in column 1 do not look at interaction terms and simply reflect the fact that firms in rating category A are less likely to be liquidated than firms rated B and firms rated C, as already hinted by Table 3. Column 2 adds the dummy $D_i$ which, as expected, is positively correlated with the likelihood of wining-up. The last three columns of Table 6 interact the dummy variable $D_i$ with the firm's rating category, as indicated in equation (13), restricting attention to firms in sectors with high (column 4) and low $RZ$ indicators (column 5).

[15] In the model, the channel whereby the reallocation effect operates, is by deterring entry. Unfortunately we cannot directly test for firm entry using our firm-level dataset as we do not observe small firms in our dataset. However, we know about aggregate entry and exit for each sector in each year. And ranking sector-year points on the entry and exit scales -correcting for year fixed effects - we can show that entry and exit aat sector level are positively correlated (see McGowan et al. 2017a,b and Figure A4 in the Appendix).

[16] Table A3 in the Appendix shows the results from the same regression but defining $D_i$ using the productivity distribution in 2004 (in which case $D_i$ is time invariant). The joint distribution of $D_{i,t-1}$ and rating category is reported in Figure A3 in the Appendix.

Table 6: Liquidation and Rating

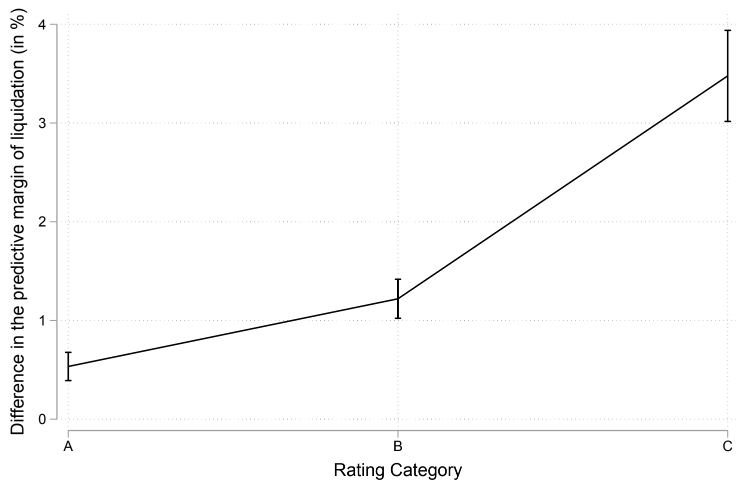
| Dependent variable | Liquidation at $t+2$ dummy | | | | |
|---|---|---|---|---|---|
| | **(1)** | **(2)** All | **(3)** | **(4)** High RZ | **(5)** Low RZ |
| **Rating Category** | | | | | |
| A | -0.016*** | -0.014*** | -0.014*** | -0.016*** | -0.012*** |
| | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) |
| B (ref) | | | | | |
| C | 0.051*** | 0.049*** | 0.043*** | 0.044*** | 0.043*** |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) |
| $log(L)$ | -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. | | 0.025*** | | | |
| | | (0.001) | | | |
| Rat. Cat. A $\times$ Low Prod | | | 0.011*** | 0.014*** | 0.007*** |
| | | | (0.001) | (0.002) | (0.002) |
| Rat. Cat. B $\times$ Low Prod | | | 0.019*** | 0.022*** | 0.015*** |
| | | | (0.002) | (0.002) | (0.002) |
| Rat. Cat. C $\times$ Low Prod | | | 0.050*** | 0.064*** | 0.034*** |
| | | | (0.004) | (0.005) | (0.005) |
| Fixed Effects | $s \times t$ | $s \times t$ | $s \times t$ | $\times t$ | $s \times t$ |
| $R^2$ | 0.035 | 0.038 | 0.039 | 0.039 | 0.040 |
| Observations | 322,165 | 322,165 | 322,165 | 203,578 | 118,587 |

**Notes**: This table shows results from an estimation of equation (13). The dependent variable is a binary variable that takes the value 1 if the firm exits from liquidation at $t+2$. Variable Low Prod. corresponds to $D_{i,t-1}$ in equation (13) and is a binary variable taking the value 1 if the firm is below its sector's $25^{th}$ percentile at $t-1$. Coefficients are obtained using an OLS estimator and standard errors are heteroskedastic robust, clustered at the firm level and reported in parentheses.

These results suggest that particularly the less 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, relaxing credit constraints allows particularly the less productive firms to remain in the market.

Recall that these are estimates of a linear model, and parameters should not be considered as marginal probabilities. We now turn to a more 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 thus estimate by maximum likelihood the

Figure 2: Survival model regression results




**Notes**: This plot presents the differences between the predictive margins of liquidation of low productivity firms versus more productivity firms at any given rating $i \in A, B, C$. Low productive firms are defined using the variable $D_{i,t-1}$ as in equation (13). $D_{i,t-1}$ is a binary variable taking the value 1 if the firm is below its sector's $25^{th}$ percentile at $t-1$

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 at date $t$ for firm $i$), $(p, \lambda)$ are the parameters of the Weibull distribution, $x_i$ is the set of covariates presented in equation (13) and $\beta$ the vector of corresponding coefficients ($\alpha_k, \beta_k$ and $\gamma$). 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 in predictive margins of liquidation for low versus high productivity firms at the rating levels $i \in A, B, C$. Among A rated firms, both low and high productivity firms have a high survival probability and the difference in survival probabilities between low and high productivity firms is small. However, when moving to C-rated firms, both low and high productivity firms will exit more than their A-rated counterparts, but in addition the ratio of exit rates of low versus high productivity firms, is much higher than when looking at the A-rated counterparts. The corresponding predictive margins of default are reported in Table 7.

Table 7: PREDICTIVE MARGINS OF DEFAULT

| $D_{i,t-1}$ | Rating | Margin of Default |
|---|---|---|
| 0 | A | 0.10% |
| 1 | A | 0.64% |
| 0 | B | 0.66% |
| 1 | B | 1.88% |
| 0 | C | 2.39% |
| 1 | C | 5.87% |

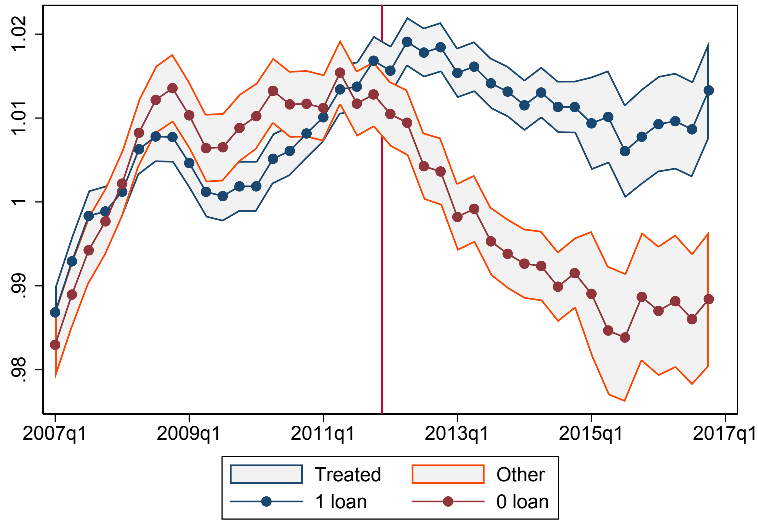
**Notes**: Predictive Margins represent the marginal impact on the probability of default of being a low productivity or a more productivity firm with a rating i. Low productive firms are defined using the variable $D_{i,t-1}$ as in equation (13). $D_{i,t-1}$ is a binary variable taking the value 1 if the firm is below its sector's $25^{th}$ percentile at $t-1$

## 5.3 The ACC program as quasi-experiment

### 5.3.1 The Eurosystem's Additional Credit Claims (ACC) program

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, only 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 then it was implemented in February 2012. This program led to an extension of this eligibility rule to include firms rated 4 (corresponding to part of our category B). This in turn generated a discontinuity in credit access for firms that were rated 4 at the end of 2011. While other policy measures in the Euro Area were implemented at the same time, the ACC program is the only program that generated a difference between firms rated 4 and firms rated $5^+$ within category B. We refer to firms rated 4 as the *treated* firms and to firms rated 5 as the *control* firms within category B (see Cahn et al., 2017 and Mesonnier et al., 2017 for recent studies using the ACC as a quasi-natural experiment).

Figure 3: Evolution of the stock of credits and ACC program




**Notes**: Vertical line corresponds to the implementation of the ACC program in 2012q1. Treatment group corresponds to firms with a rating 4 in 2011, control group contains firm with a rating $5^+$ in 2011. Log of the stock of new credit divided by revenue has been standardized so as to be equal to 1 on average between 2007 and 2008. 95% confident interval are reported. Quarterly data taken from the credit register from 2006 to 2016.

We thus use the introduction of the ACC program as an event that exogenously reduced financial constraints for firms rated 4 at the end of 2011 but not firms rated $5^+$, to perform a diff-in-diff regression exercise.[17] To show that this quasi-natural experiment indeed impacted credit supply to treated 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 between firms rated 4 and firms rated $5^+$ in 2011. However, the loans trends started to significantly diverge shortly after the program was established.

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

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

- Reduce the likelihood of exiting the market through liquidation for treated firms, and the

[17]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.

more so for treated firms with low productivity.

#### 5.3.2 Effect of ACC on TFP growth

We restrict attention to firms that are highly similar and belong to the rating category B. We then estimate the equation:

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

where $g_{i,t}$ is TFP growth of firm $i$ at date $t$, $Treated_i$ is a 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 years of the ACC program onwards, $X_{i,t}$ a vector of observed characteristics, $\nu_{s,t}$ is a sector×year fixed effect and $\nu_i$ is a firm fixed effect (this fixed is colinear to the dummy $Treated_i$ thus we do not include an independent $Treated_i$ term in the regression). 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 attention to sectors that are above (resp. below) the median in terms of their level of external financial dependence. As expected, the estimate of $\beta_1$ from equation (15) is positive and significant in column 1, and this is primarily driven by more financially dependent sectors. In the remaining columns, we show that our effect is indeed due to the ACC program shock: columns 4 and 5 consider two alternative treatment and control groups (respectively 3 and $4^+$ and 5 and 6) and show no significant effect. Column 6 replaces the variable (post ACC) by a dummy for $t$ being larger than 2007 and here again we see no significant effect: all these placebo tests imply no significant response for our variable of interest.

These results provide causal evidence of a direct positive effect of credit access on firm-level productivity growth.

#### 5.3.3 Effect of ACC on exit

Here, we estimate the following equation:

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

Note that we do not directly interact credit access (or our instrument for it) with the firm's

Table 8: ACC PROGRAM AND PRODUCTIVITY SHOCK

| Dependent variable | TFP growth (in %) | | | | | |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| Treated×(post ACC) | 0.776** | 0.994** | 0.394 | -0.363 | 1.387 | 0.319 |
| | (0.372) | (0.487) | (0.573) | (0.294) | (1.155) | (0.495) |
| $log(L)$ | -11.959*** | -11.114*** | -13.229*** | -11.354*** | -13.058*** | -11.945*** |
| | (0.599) | (0.778) | (0.942) | (0.574) | (1.237) | (0.599) |
| Fixed Effects | $i+s\times t$ | $i+s\times t$ | $i+s\times t$ | $i+s\times t$ | $i+s\times t$ | $i+s\times t$ |
| $R^2$ | 0.102 | 0.099 | 0.108 | 0.106 | 0.128 | 0.102 |
| Observations | 93,000 | 57,373 | 35,625 | 93,101 | 23,156 | 93,000 |

**Notes**: This table shows results from estimating equation (15). The dependent variable, TFP growth, is given in percentage. Columns 1 define the treatment group (captured by the dummy $Treated$ as firms with a rating 4 in 2011 and the control group as firms with a rating $5^+$ in the same year. Columns 2 and 3 show results from estimating the same model respectively for above and below median sectors in terms of external financial dependency (based on the RZ indicator). Other columns report results from placebo regressions. Columns 4 and 5 consider two alternative of these treatment and control groups (respectively 3 and $4^+$ and 5 and 6). Column 6 replaces the variable (post ACC) by a dummy for t being larger than 2007. All regressions have individual and year×sector fixed effects. Heteroskedastic robust and standard errors clustered at the firm level are reported in parentheses.

level of productivity as we did when performing the OLS analysis, but instead we run the equation separately: (i) for all firms (columns 1 and 2 of Table 9); (ii) for low (resp. high) productive firms (columns 3 and 4 of Table 9). Note that here we consider firms' productivity levels in 2011, just before the ACC shock.[18]

We see that the coefficient of interest (i.e. $\beta_1$ 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 among firms with rating 4 (the treated firms) it is those with lower productivity in 2011 which saw their exit rates reduced by a larger extent following the introduction of the AC program.

Finally, 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.

[18] The reason is that we already impose that the firm be in our 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 require that these firms be in the dataset for a long period and thus that they should have survived for that year onwards. This in turn would force us to reduce our sample significantly, and to bias it against lower productivity/more credit constrained firms.

Table 9: ACC PROGRAM AND RISK OF DEFAULT

| Dependent variable | Default | | | | | |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| (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**: This table reports results from estimating equation (16). Quantiles of productivity are calculated according to the individual level of TFP in 2011 at the sectoral level. Columns 1 and 2 consider all firms in the control and treatment groups, columns 3, 5 and 6 only consider firms that are in the bottom 25% in terms of their productivity level in 2011 and columns 4 focuses on firm that are above this level. Columns 5 and 6 in addition restrict to above (resp. below) median firms in terms of their $RZ$ index. All regressions have a year×sector fixed effects. Heteroskedastic robust and standard errors clustered at the firm level are reported in parentheses.

# 6 Conclusion

In this paper we have identified two counteracting effects of credit access on productivity growth: first, a positive direct effect of credit access on (incumbent) firms' productivity growth which reflects the fact that better access to credit makes it easier for entrepreneurs to innovate; second, a negative reallocation effect of credit access working through the exit rate of incumbent firms and its effect on entry of potentially more efficient innovators. We developed a simple model of firm dynamics and innovation-led growth with credit constraints, to generate these two effects and then we showed that the combination of the two effects can result in an aggregate inverted-U relationship between credit access and productivity growth. We then used a comprehensive French firm-level dataset to first provide evidence of such an inverted-U relationship in a cross-sector panel regression. Then we moved to firm-level analysis to provide supporting evidence of the two counteracting effects of credit access on aggregate productivity growth, respectively working through the productivity growth and the exit rates of incumbent firms. Finally, we used the 2012 Eurosystem's Additional Credit Claims (ACC) program as a quasi-experiment, to argue that the effects of credit access on the productivity growth and exit rates of incumbent firms are causal: namely, incumbent firms directly affected by this program - the treated firms - experienced higher productivity growth post-ACC that similar firms not affected by the program - the control firms -; moreover, treated firms also experienced lower exit rates, particularly the least productive firms among them, compared to control firms between before and after the introduction of the ACC program.

A first extension of the analysis in this paper, would be to look at firms and sectors in other countries: in which countries and/or sectors are we most likely to observe the downward-sloping part of the inverted-U?

A second extension would be to analyze the implications of this inverted-U relationship for the conduct of fiscal and monetary policy over the business cycle. Our analysis points to a potentially negative growth effect of maintaining low interest rates in good times.

Third, our analysis also has implications for the debate on secular stagnation. The decline in productivity growth in most advanced countries since the 1970s may indeed 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 in the last decade. The increase of real interest rate expected in the recovery phase could then contribute to productivity gains through cleansing mechanisms. Hence, a natural next step would be to test the relationship between credit access and productivity growth over longer time-periods, and to look at how much of the observed productivity slowdown can actually be explained by the observed decrease in interest rates since the 1970s. These and other extensions of the analysis in this paper, are left for future research.

# References


Acemoglu, D., U. Akcigit, H. Alp, N. Bloom, and W. R. Kerr (2018): "Innovation, Reallocation, and Growth," *American Economic Review*, forthcoming.

Aghion, P., U. Akcigit, and P. Howitt (2015): "Lessons from Schumpeterian growth theory," *The American Economic Review*, 105, 94–99.

Aghion, P., P. Askenazy, N. Berman, G. Cette, and L. Eymard (2012): "Credit constraints and the cyclicality of R&D investment: Evidence from France," *Journal of the European Economic Association*, 10, 1001–1024.

Aghion, P., E. Farhi, and E. Kharroubi (2017): "On the Interaction Between Monetary Policy, Corporate Balance Sheets and Structural Reforms," Tech. rep., Harvard University.

Aghion, P. and P. Howitt (2009): *The Economics of Growth*, MIT Press.

Akcigit, U. and W. R. Kerr (2010): "Growth through heterogeneous innovations," Tech. Rep. 16443, National Bureau of Economic Research.

——— (2018): "Growth through heterogeneous innovations," *Journal of Political Economy*, forthcoming.

Banque de France (2017): "La Cotation Banque de France : Evaluation des Performances 2016," Publication interne, Banque de France.

Beck, T. and R. Levine (2018): *Handbook of Finance and Development*, Edward Elgar.

Besley, T., I. Roland, and J. Van Reenen (2018): "The Aggregate Effects of Credit Market Frictions: Evidence from Firm-level Default Assessments," Tech. rep., mimeo.

Cahn, C., A. Duquerroy, and W. Mullins (2017): "Unconventional Monetary Policy and Bank Lending Relationships," Working Paper 659, Banque de France.

Cecchetti, S. G. and E. Kharroubi (2015): "Why does financial sector growth crowd out real economic growth?" Working Paper 490, Bank for International Settlment.

Cette, G., J. Fernald, and B. Mojon (2016): "The pre-Great Recession slowdown in productivity," *European Economic Review*, 88, 3–20.

Duval, R., G. Hong, and Y. Timmer (2017): "Financial Frictions and the Great Productivity Slowdown," Working Paper 17/129, IMF.

Gopinath, G., Ş. Kalemli-Özcan, L. Karabarbounis, and C. Villegas-Sanchez (2017): "Capital allocation and productivity in South Europe," *The Quarterly Journal of Economics*, 132, 1915–1967.

Gorton, G. and G. Ordoez (2014): "Collateral Crises," *American Economic Review*, 104, 343–78.

Gropp, R., J. Rocholl, and V. Saadi (2017): "The Cleansing Effects of Banking Crisis," Unpublished manuscript.

King, R. G. and R. Levine (1993): "Finance and growth: Schumpeter might be right," *The Quarterly Journal of Economics*, 108, 717–737.

Klette, T. J. and S. Kortum (2004): "Innovating firms and aggregate innovation," *Journal of Political Economy*, 112, 986–1018.

Levine, R. (1997): "Financial development and economic growth: views and agenda," *Journal of Economic Literature*, 35, 688–726.

——— (2005): "Finance and growth: theory and evidence," *Handbook of economic growth*, 1, 865–934.

Levinsohn, J. and A. Petrin (2003): "Estimating Production Functions Using Inputs to Control for Unobservables," *The Review of Economic Studies*, 70, 317–341.

Manaresi, F. and N. Pierri (2017): "Credit Constraints and Firm Productivity: Evidence from Italy," Mo.Fi.R. Working Papers 137, Money and Finance Research group (Mo.Fi.R.) - Univ. Politecnica Marche - Dept. Economic and Social Sciences.

McGowan, M. A., D. Andrews, and V. Millot (2017a): "insolvency Regimes, Zombie Firms and Capital Reallocation," Working Paper 1399, OECD.

——— (2017b): "The Walking Dead? Zombie Firms and Productivity Performance in OECD countries," Working Paper 1372, OECD.

Mesonnier, J.-S., C. ODonnell, and O. Toutain (2017): “The Interest of Being Eligible,” Working papers 636, Banque de France.

Popov, A. (2017): “Evidence on finance and economic growth,” Working Paper 2115, ECB.

Rajan, R. G. and L. Zingales (1998): “Financial Dependence and Growth,” *The American Economic Review*, 88, 559–586.

Reis, R. (2013): “The Portugese Slump and Crash and the Euro Crisis,” *Brookings Papers on Economic Activity*, 44, 143–210.

# A Additional results

Table A1: Descriptive Statistics for the Manufacturing Sectors

| Industry | L | Y | Age | g | r | Liquidation | Firms |
|---|---|---|---|---|---|---|---|
| Food | 17 | 715 | 15.5 | 1.36 | 2.8 | 8.28 | 6,622 |
| Beverage | 10 | 854 | 22 | 1.17 | 2.9 | 2.03 | 640 |
| Textile | 20.7 | 880 | 19.5 | 0.85 | 3.16 | 19.04 | 1,224 |
| Apparel | 14 | 698 | 17 | -0.53 | 3.31 | 26.68 | 1,233 |
| Leather and Shoe | 26.1 | 1,049 | 20 | 2.41 | 3.7 | 17.34 | 369 |
| Wood | 14.2 | 572 | 19 | 2.91 | 2.72 | 15.04 | 2,341 |
| Paper and Pulp | 26.8 | 1,135 | 20 | 2.93 | 3.04 | 10.36 | 927 |
| Printing | 14.2 | 623 | 19.5 | 2.24 | 3.34 | 21.63 | 2,566 |
| Chemical | 26 | 1,646 | 19 | 1.73 | 2.76 | 7.4 | 1,541 |
| Pharmaceutical | 55.8 | 3,963 | 19.2 | 4.54 | 3.2 | 3.45 | 348 |
| Rubber and Plastic | 22.5 | 1,135 | 18.5 | 1.97 | 3.02 | 12.37 | 2,740 |
| Non-metallic Products | 14.8 | 817 | 20 | 1.22 | 3.5 | 10.26 | 2,066 |
| Metallurgy | 33.3 | 1,628 | 17 | 1.29 | 2.45 | 17.28 | 706 |
| Metallic Products | 16.5 | 827 | 18 | 1.46 | 3.07 | 14.73 | 8,851 |
| Computer Products | 22 | 967 | 18 | 8.42 | 2.45 | 13.62 | 1,490 |
| Electronic Equipment | 21.5 | 1,275 | 18 | 0.13 | 3.32 | 13.18 | 1,161 |
| Machinery and Equipment | 18.8 | 1,090 | 18 | 0.94 | 3.16 | 13.24 | 3,255 |
| Automotive | 24 | 1,225 | 17.5 | -0.45 | 2.84 | 13.83 | 969 |
| Other Transportation Equipment | 36.6 | 1,910 | 13 | 0.12 | 2.53 | 17.2 | 378 |
| Furniture | 17 | 795 | 17 | -1.44 | 3.5 | 27.12 | 1,309 |
| Other Manufacturing | 15.6 | 910 | 18 | -0.6 | 3.22 | 10.54 | 1,480 |
| Repair of Machinery | 13 | 762 | 15 | -0.44 | 3.28 | 14.61 | 4,756 |

**Notes:** This table reports the sectoral median level of (L) employment, real value added (Y, in thousand euros of 2014), Age, TFP growth (g, in %), real effective interest rate of new credits with a maturity exceeding one year (r, in %) and percentage of firms that are liquidated between 2004 and 2016. The sample is the same as in Table 2: private manufacturing firms with annual sales exceeding $750,000$ euros or with outstanding credit exceeding $380,000$ euros from the years 2004 to 2016. All the variables except liquidation have been averaged by firm before we compute the median value by sector. The tobacco and the processing and coking industries are dropped throughout because of the little amount of firms in those sectors.

Figure A1: Share of Manufacturing Firms by Birth Cohort

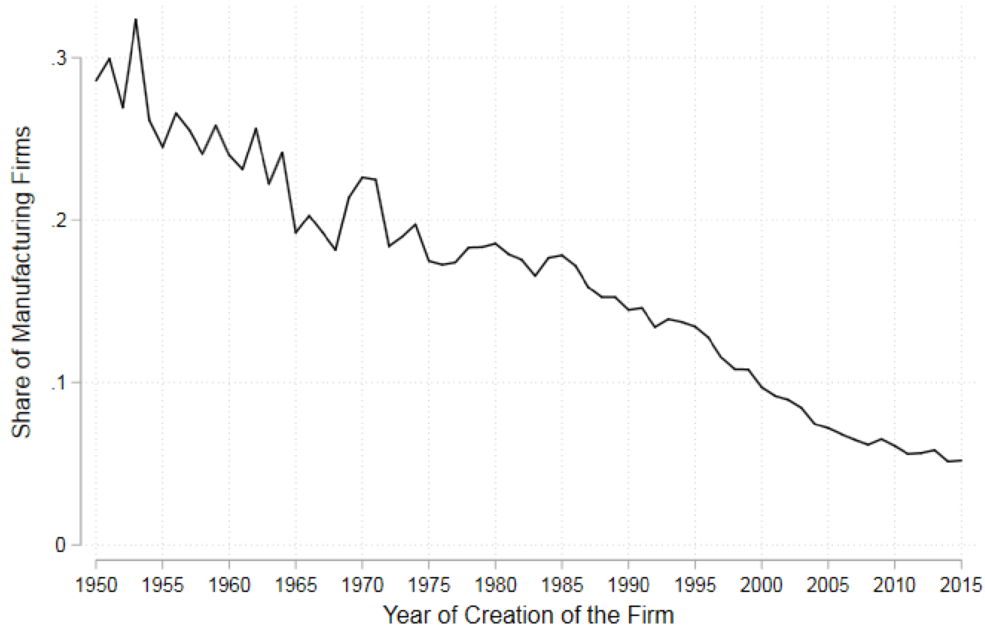



Figure A2: Daily EONIA rate and average yearly rate, 2000-2017

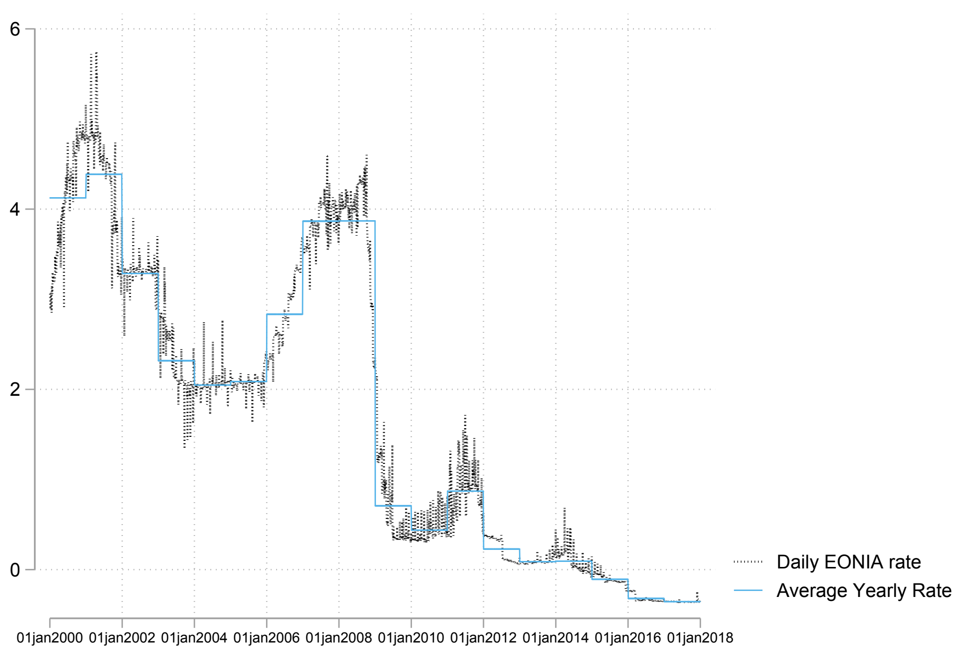
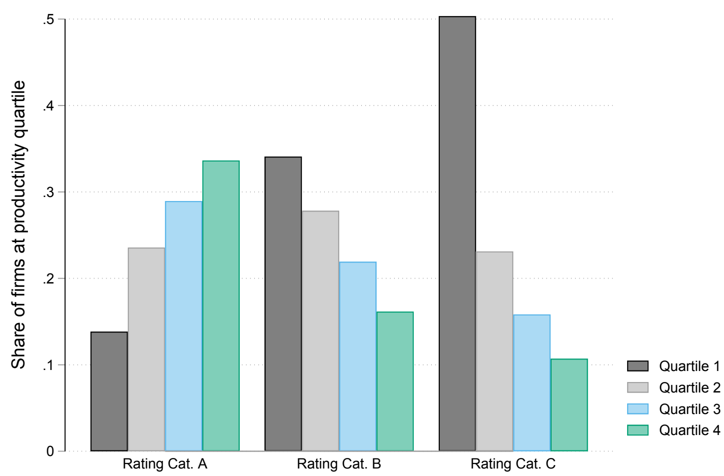


Table A2: RATING CATEGORIES AND TFP

| Dependent variable | Investment rate | | | Delta Investment rate | | |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| **Rating Category** | | | | | | |
| A | 0.038*** | 0.036*** | 0.033*** | 0.013*** | 0.024*** | 0.026*** |
| | (0.002) | (0.003) | (0.003) | (0.002) | (0.003) | (0.003) |
| B (ref) | | | | | | |
| C | -0.019*** | -0.021*** | -0.021*** | -0.005 | -0.008 | -0.009 |
| | (0.004) | (0.006) | (0.006) | (0.004) | (0.006) | (0.006) |
| ($L_{t-1}$) | -0.001 | -0.087*** | -0.087*** | -0.005*** | -0.112*** | -0.111*** |
| | (0.001) | (0.006) | (0.006) | (0.001) | (0.007) | (0.007) |
| Age | -0.001*** | -0.002*** | | 0.001*** | 0.002*** | |
| | (0.000) | (0.000) | | (0.000) | (0.000) | |
| Fixed Effects | $s \times t$ | $i$ | $i + s \times t$ | $s \times t$ | $i$ | $i + s \times t$ |
| $R^2$ | 0.007 | 0.218 | 0.220 | 0.002 | 0.076 | 0.078 |
| Observations | 277,226 | 272,885 | 272,885 | 276,558 | 272,242 | 272,242 |

**Notes**: This table shows results from an estimation of investment rate (defined as the ratio of investment over current capital) and its first difference on a dummy for each rating category. Coefficients are obtained using an OLS estimator and standard errors are heteroskedastic robust, clustered at the firm level and reported in parentheses.

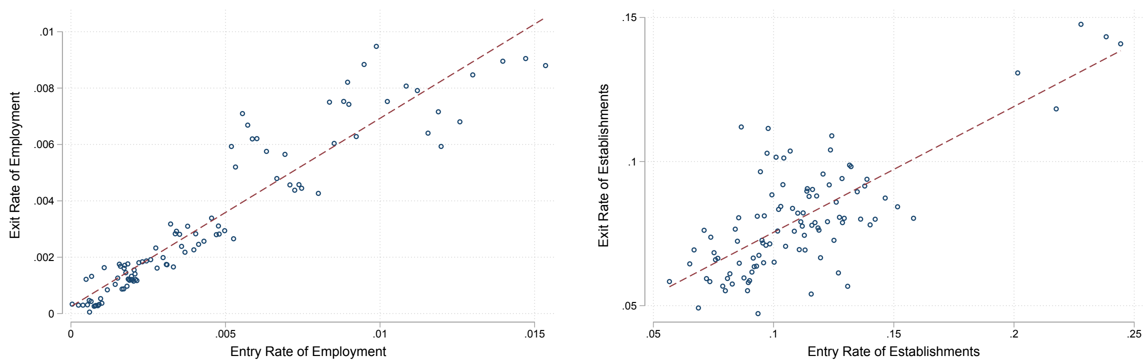
Figure A3: Share of firms by quartile of productivity, at different rating categories




**Note:** Each year and for each sector, we split firms into 4 productivity quantiles based on their previous year's TFP level. This graph report the share of firms in these 4 quartiles for each of our 3 rating categories A, B and C.

Figure A4: Correlation between entry and exit rates

(a) By employment (b) By establishment




**Note:** Each dot represents a 2-digit manufacturing sector in a specific year from 2004 to 2014. Left-hand side figure plots the average entry rate of employment in the sector against the average exit rate of employment, both variables have been residualized on a year fixed effect. Entry (resp exit) rates are defined as the ratio between new employment at $t$ and the stock of employment at $t-1$. Right-hand side panel does the same but uses entry and exit rates of establishment. Data have been obtained directly from the INSEE and are based on administrative data (DADS).

Table A3: 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) |
| B (ref) | | | | | |
| C | 0.057*** | 0.056*** | 0.051*** | 0.050*** | 0.052*** |
| | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) |
| $Log(L)$ | -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.