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Credit Constraints and the Cyclicality of R&D Investment: Evidence from France*

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Abstract

We use a French firm-level data set containing 13,000 firms over the period 1993-2004 to analyze the relationship between credit constraints and firms' R&D behavior over the business cycle. Our main results can be summarized as follows: (i) the share of R&D investment over total investment is countercyclical without credit constraints, but it becomes less countercyclical as firms face tighter credit constraints; (ii) this result is magnified for firms in sectors that depend more heavily upon external finance, or that are characterized by a low degree of asset tangibility ; (iii) in more credit constrained firms, R&D investment share plummets during recessions but does not increase proportionally during upturns; (iv) average R&D investment and productivity growth are more negatively correlated with sales volatility in more credit constrained firms.

JEL classification: E22, E32, O16, O30, O32.
Keywords: business cycles, R&D, credit constraints, volatility.

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I Introduction

A Schumpeterian view of business cycles and growth is that recessions provide a cleansing mechanism for correcting organizational inefficiencies and for encouraging firms to reorganize, innovate or reallocate to new markets. The cleansing effect of recessions is also to eliminate those firms that are unable to reorganize or innovate. Schumpeter[1] himself would summarize that view as follows; "[Recessions] are but temporary. They are means to reconstruct each time the economic system on a more efficient plan". This of course assumes that firms can always borrow enough funds to either reorganize their activities or move to new activities and markets. Investment choices are indeed dictated by an opportunity-cost effect: namely, the opportunity cost of long-term innovative investments instead of short-term capital investments, is lower in recessions than in booms. Hence, the share of long-term investment in total investment should be countercyclical, whereas the share of short-term investment is procyclical (see Hall (1993), Gali and Hammour (1992), Aghion and Saint-Paul (1998), Bean (1990), Bloom (2007)).

However, this is only true to the extent that firms are not credit constrained. As emphasized by Aghion *et al.* (2005), henceforth AABM, things become quite different when credit market imperfections prevent firms from innovating and reorganizing in recessions. In particular, suppose that firms can choose between short-run capital investment and long-term R&D investment, that innovating requires that firms survive short-run liquidity shocks, and that to cover liquidity costs firms can rely only on their short-run earnings plus borrowing. Whenever the firm is hit by a bad (idiosyncratic or aggregate) shock, its current earnings are reduced, and therefore so is the firms' ability to borrow in order to innovate. This in turn implies that a negative shock should hit R&D investments and innovation more in firms that are more credit constrained. In other words, R&D investments should be expected to be less countercyclical in firms facing tighter credit constraints.

In this paper, we test this prediction using a French firm-level panel data set that contains information both, on the extent of credit constraints at the firm level each year, and on R&D investments by the firm, relative to total investment. The firm-level database we use has been collected by the Banque de France. The sample includes about 13,000 firms (all of them having at least one time a positive R&D investment) and covers the period 1993-2004. The database contains an important number of small and medium firms that are particularly prone to be hit by credit constraints, and are thus especially relevant for the study of the above-mentioned mechanisms.

We regress firm R&D over total investment on firm sales and its interaction with credit constraints. Our main results can be summarized as follows: (i) the share of R&D investment over total investment

[1] See Schumpeter (1942).

is countercyclical without credit constraints, and it becomes less countercyclical as firms face tighter credit constrained; (iii) this effect is only observed during downturns: namely, in presence of credit constraints, R&D investment share plummets during recessions but it does not increase proportionally during upturns; (iv) the level of R&D investment is lower in more credit constrained firms whatever the firm's position within the business cycle - but it decreases more during recessions.

These results has important implications at the macroeconomic level. First, because by preventing firms from investing in R&D during downturns, credit constraints decrease average R&D investment and productivity growth. Second, because without credit constraints, the countercyclicality of R&D investment has a smoothing effect on aggregate volatility. By preventing R&D investment from being countercyclical, credit constraints may also prevent R&D from having this smoothing effect, thus amplifying volatility. The existence of credit constraints may thus increase both volatility and its negative effect on average productivity growth. The last part of this paper provides empirical evidence supporting these effects.

This paper relates to a broader literature on cycles, innovation and growth. The theoretical papers that are most closely related to our approach in this paper are Hall (1991), Gali and Hammour (1992), Caballero and Hammour (1994), Aghion and Saint-Paul (1998), Francois and Lloyd-Ellis (2003), Comin and Gertler (2006), and Barlevy (2004, 2007). All these papers take a Schumpeterian approach to the relationship between growth and cycles, however they do not emphasize credit constraints. The empirical literature on the subject starts with Ramey and Ramey (1995) who provide cross-country evidence of a negative relationship between volatility and growth. More closely related to the analysis in this paper is AABM. Based on cross-country panel data over the period 1960-2000, AABM show that structural investment (another proxy for growth-enhancing investment) is less countercyclical in countries with lower ratios of credit to GDP, and that the correlation between macroeconomic volatility (measured as in Ramey and Ramey (1995) by the variance of growth rate) and average growth, is more negative the lower financial development. However, unlike in this paper, the data in AABM do not include R&D investments, and moreover credit constraints are not measured at the firm level. Prior evidence on R&D investments over the cycle is provided by Griliches (1990), Comin and Gertler (2006), and Barlevy (2007), although not in relation to firms' credit constraints[2].

The paper is organized as follows. Section 2 presents a simple model to derive our main predictions. Section 3 presents the data and the measurement variables, and in particular our measure of credit constraint. Section 4 presents the key results. Section 5 discusses the robustness of our results and their implications for productivity growth and volatility, and it concludes.

[2]Barlevy (2007) finds no evidence of current cash flows affecting how firms' current R&D investments respond to the business cycle. However, in Barlevy's own estimations, lagged cash flows turn out to significantly affect how current R&D investment reacts to the firm's current position in the business cycle.

II Model

1 Basic environment

There is a continuum of two period lived risk-neutral entrepreneurs who maximize their wealth. An entrepreneur faces a sales shock a_t at time t and a_{t+1} at time $t+1$, where

$$a_t \in \{\underline{a}, \overline{a}\},$$

and

$$\begin{aligned} p &= \Pr(a_{t+1} = \overline{a}/a_t = \overline{a}) \\ &= \Pr(a_{t+1} = \underline{a}/a_t = \underline{a}) \end{aligned}$$

is strictly less than one but greater than 1/2 so that there is some persistence to a sales shock over time.

At the beginning of her first period, an entrepreneur born at date t decides about: (i) short-run capital investment k_t, which yields short run profit $a_t k_t$ at cost $\frac{1}{2}dk_t^2$ at the end of the first period, and; (ii) long-term R&D investment z_t , which yields an innovation value v_{t+1} equal to the expected productivity $E(a_{t+1}/a_t)$ in period $(t+1)$ with probability z_t in the second period, at cost $\frac{1}{2}cz_t^2$. Credit market imperfections may prevent a firm with short-run profit flow $a_t k_t$ from investing more than $\mu a_t k_t$ in R&D, where $\mu \geq 1$ measures the extent to which the firm can borrow using its first period return as collateral.

2 Profit maximization and optimal investments

Consider first the benchmark case where the entrepreneur is not credit constrained. Then she will choose k and z to

$$\max_{k,z}\{a_t k + E(a_{t+1}/a_t)z - \frac{1}{2}dk^2 - \frac{1}{2}cz^2\},$$

which yields

$$dk = a_t; \tag{1}$$

$$cz = E(a_{t+1}/a_t) = pa_t + (1-p)a_{-t}, \tag{2}$$

where

$$a_{-t} \neq a_t$$

In particular, given that $p < 1$, the ratio

$$\frac{z}{k} = \frac{d}{c}\frac{E(a_{t+1}/a_t)}{a_t} = \frac{d}{c}[p + (1-p)\frac{a_{-t}}{a_t}] \tag{3}$$

is countercyclical, that is, lower when sales are high with $a_t = \overline{a}$ than when sales are low with $a_t = \underline{a}$. This is the opportunity cost effect already mentioned in the introduction.

Now, consider the case where the entrepreneur is credit-constrained. Then she will choose k and z to

$$\max_{k,z}\{a_t k + E(a_{t+1}/a_t)z - \frac{1}{2}dk^2 - \frac{1}{2}cz^2\}$$

$$s.t. \qquad z \leq \mu k a_t \ .$$

The credit-constraint is binding whenever the equilibrium R&D level in the absence of credit constraint, is higher than $\mu k a_t$ in equilibrium, that is, whenever

$$\frac{E(a_{t+1}/a_t)}{c} > \mu\frac{(a_t)^2}{d}.$$

This latter condition, which can be reexpressed as

$$\frac{1}{c}[p + (1-p)\frac{a_{-t}}{a_t}] > \mu\frac{a_t}{d}, \tag{4}$$

is more likely to be satisfied when the firms faces a low sales shock (with $a_t = \underline{a}$ and $a_{-t} = \overline{a}$) than when it faces a high sales shock (with $a_t = \overline{a}$ and $a_{-t} = \underline{a}$).

Suppose first that the credit constraint binds only when sales are low. Then the ratio of R&D over capital investment $\frac{z}{k}$ is necessarily procyclical. To see this, note that: (i) when $a_t = \overline{a}$, this ratio is unconstrained and thus from (3) it is equal to:

$$(\frac{z}{k})^{higha} = \frac{d}{c}[p + (1-p)\frac{\underline{a}}{\overline{a}}];$$

(ii) when $a_t = \underline{a}$ the credit constraint is binding so that the R&D/capital ratio is equal to:

$$(\frac{z}{k})^{lowa} = \mu\underline{a};$$

(iii) our assumption that (4) is satisfied for $a_t = \underline{a}$, which immediately implies that:

$$(\frac{z}{k})^{lowa} < (\frac{z}{k})^{higha}.$$

Another predictions in this case is that a lower μ reduces $(\frac{z}{k})^{lowa}$ without affecting $(\frac{z}{k})^{higha}$. Thus, lowering μ will result in a lower equilibrium R&D investment reduced in a low sales shock, whereas the R&D investment is unchanged in a high sales shock.

Overall, *the R&D/capital ratio will be less countercyclical in a firm facing tighter credit constraints, and that firm will also invest relatively less in R&D on average over time.* These predictions will be validated by our empirical analysis in the next sections.

Now, suppose that condition (4) is always binding. Then the equilibrium R&D/capital ratio remains procyclical, with

$$(\frac{z}{k})^{lowa} = \mu\underline{a} < (\frac{z}{k})^{higha} = \mu\overline{a}.$$

However, in this case, a lower μ will reduce the R&D/capital ratio $\frac{z}{k}$ more when the firm faces high sales (when $a_t = \overline{a}$) than when it faces low sales ($a_t = \underline{a}$) since

$$\frac{d}{d\mu}[(\frac{z}{k})^{higha} - (\frac{z}{k})^{lowa}] = \overline{a} - \underline{a} > 0.$$

This case is not the most plausible, as we can expect firms to be less credit-constrained in high than in low-sales states. And indeed our empirical analysis will not support this latter prediction that tightening credit constraints should reduce the R&D share of investment by more in upturns than in downturns.

To complete our analysis of the model, we can derive the equilibrium R&D investment under high and low current sales respectively. If the credit constraint does not bind, then from (2) we have:

$$z = \frac{E(a_{t+1}/a_t)}{c}.$$

And if it binds one can show that[3]:

[3]To see this, note that when the credit constraint binds, we have

$$z = \mu k a_t$$

so that the optimal capital investment k solves:

$$\max_k \{a_t k + E(a_{t+1}/a_t)\mu k a_t - \frac{1}{2}dk^2 - \frac{1}{2}c(\mu k a_t)^2\}.$$

From first order condition we get:

$$k = \frac{1}{d + c(\mu a_t)^2} a_t[1 + \mu E(a_{t+1}/a_t)]$$

and therefore

$$\begin{aligned} z &= \mu k a_t \\ &= \frac{\mu}{d + c(\mu a_t)^2}(a_t)^2[1 + \mu E(a_{t+1}/a_t)]. \end{aligned}$$

$$z = \frac{1}{d + c(\mu a_t)^2}\mu(a_t)^2[1 + \mu E(a_{t+1}/a_t)].$$

It then follows that R&D is procyclical when the credit constraint binds in the low sales state. This is obvious when the firm is also constrained in the high sales state, as

$$\frac{\overline{a}^2}{d + c(\mu\overline{a})^2} > \frac{\underline{a}^2}{d + c(\mu\underline{a})^2}$$

and

$$[1 + \mu(p\underline{a} + (1-p)\overline{a})] < [1 + \mu(p\overline{a} + (1-p)\underline{a})]$$

when $p > 1/2$. It is a fortiori true when the firm is constrained in the low sales state only since the credit constraint affects the R&D investment primarily.

3 Main theoretical predictions

The main predictions that emerge from our analysis in this section can be summarized as follows:

1. The more credit constrained the firm is, the less countercyclical its (relative) R&D investment (in the sense that it reacts more positively to the firm's current sales).

2. Tighter credit constraints interact with sales in an asymmetric fashion over the business cycle. In particular, starting from a situation where credit constraints are more binding in downturns, a tightening of credit-constraints or an increase in the volatility of sales, reduce the firm's R&D investment more in a downturn than it might increase it in an upturn. It thus reduces the firm's average R&D investment.

In the remaining part of the paper we take these predictions to French firm-level panel data.

III Data

Our empirical analysis merges two different French-firm-level datasets: FiBen and the payment incident dataset, which we now describe in more details.

1 The FiBEn database

Our core data comes from FiBEn, a large French-firm-level database constructed by the Banque de France. FiBEn is based on fiscal documents, including balance sheet and P&L statement, and thus contains detailed information on both flow and stock accounting variables. A subsample of FiBEn, called *Centrale des Bilans*, is available for a lower number of firms and includes additional information directly collected by the Banque de France. This additional data allow us to perform additional consistency and accuracy tests.

The FiBen database includes all French firms with sales at least equal to 75,000 euros or with credit outstanding of at least 38,000 euros; annual accounting data are then available for about 200,000 firms. In 2004, FiBEn covered 80% of the firms with 20 to 500 employees, and 98% of those employing more than 500 employees[4].

We then restrict our sample by looking only at firms that have at least one year a positive R&D investment; our sample is unbalanced and includes about 13,000 firms over the period 1993-2004. A same firm appears in our database during a seven year period on average.

[Table 1 about here]

[Table 2 about here]

Tables 1 and 2 present summary statistics for our key variables, including the R&D share of investment, and the measure of credit constraint we use in the empirical analysis; this measure, which is referred to as "payment incident", will be described and analyzed in details in two of the following subsections.

Our final sample includes an important number of small and medium firms[5], that are particularly prone to be hit by credit constraints.

2 R&D variable

Among the variables for which FiBEn data are available, we choose to concentrate on R&D investment rather than R&D expenditures as a proxy for long-term productivity-enhancing investment. R&D investments are a fraction of R&D expenditures that the firms are allowed to capitalize. There are many reasons to look at investment rather than expenditures, the main one being that expenditures are only available for a subset of big firms. Since the mechanisms we are looking at are more likely to be observed for small firms, it is more pertinent to keep these firms in the sample and look at R&D investment. This is reinforced by the fact that first, it makes the ratio of R&D investment over

[4]More than 50% of the firms in FiBEn have less than 20 employees. However, these firms are under-represented in FiBEn since their sales rarely exceed the required amount.

[5]The median size is of around 30 employees per firm.

total investment, which is central in our study, more homogenous, and second, R&D investment is much more volatile than R&D expenditures, since the latter include in an important way researchers wages that are more stable along the business cycle. Finally, another reason to use R&D investment is that it allow us to run consistency checks using the firms' balance sheet. Note that the accounting behavior of firms should not been affected by changes in the fiscal environment: the R&D fiscal rules has not been significantly altered during the studied period[6]. Using R&D investment, we check that the sectoral R&D intensity is as expected (that is the lowest for agriculture and the highest for services to businesses that include business software developments).

We also check whether our variable has a positive long-term effect on TFP growth. Table 3 shows a clear positive correlation. An increase of the ratio R&D investment over value added is associated with a significant rise of future TFP growth. The ratio R&D over total investment also has a positive and significant impact.

[Table 3 about here]

3 Description of the payment incident variable

Although direct information on credit constraints is not available, we can derive an indirect measure of credit constraints as follows. Since its introduction in 1992, all French banks have a legal obligation to report within four business days to the "Système Interbancaire de Télécompensation" anytime a firm fails to pay its trade creditors. These non-payments of trade credits are called payment incidents (henceforth PI). The Banque de France aggregates this information and makes it available to all commercial banks through a weekly paper or an electronic report automatically sent to all bank agencies. Also, since 1992, through a specific commercial network system, banks can immediately access these reports covering the last 12 months; access is through internet since 2000. The complete longitudinal dataset is available for research only at the Bank of France.

Banks are thus supposed to adapt their credit supply to this information, in particular they typically reduce future lending to firms that failed to repay their trade creditors. Our indicator for credit constraints is a binary variable equal to 1 when the firm has experienced at least one payment incident during the previous year, and to zero otherwise. This variable is easy to interpret and weakly correlated to our other key variables (see Table 14 in appendix). About 7% of firms experience each year at least one payment incident, and about one third of firms in our sample has experienced at least one payment incident over the overall period. All sectors are concerned by payment incidents, especially manufacturing motor vehicles that includes small and medium subcontractors facing the

[6]The main reforms have been implemented during the fiscal years 1990 and in 2005.

strong cyclicality of this industry. Conversely, real estate firms are less affected by the business cycle and experience fewer payment incidents (table 2).

Our descriptive statistics (table 1) shows that credit constrained firms (here defined as the firms that have experienced at least 1 payment incident during the period) display a lower ratio of R&D investment over total investments, and a higher volatility (measured by the standard deviation) of sales. This is consistent with the theoretical predictions: if credit constraints are in action, the share of productivity-enhancing investment over total investment turns less countercyclical (or even procyclical). Credit constraints thus prevent R&D from having a smoothing effect on productivity and magnifies the business cycle - sales are more volatile. We confirm these stylized facts in the next sections.

Before turning to the empirical analysis, it is important to underline that having a payment incident does not mean that the firm is in financial distress or close to bankruptcy. Around a third of all firms in our dataset experience at least once a payment incident (see Table 1), suggesting that payment incidents hit a much larger set of firms than those about to disappear. As a robustness check, we have restricted our sample to firms remaining in our sample over the entire period, or to firms which are still in the sample four years after the payment incident, i.e. firms for which having a payment incident cannot mean being close to bankruptcy. This left our results unchanged.

4 Payment Incidents as a generator of credit constraints

In this section we investigate the effect of experiencing a payment incident (PI) on future bank loans. More precisely, we study the impact of having experienced at least one PI during the two previous years ($t-1$ and $t-2$) both on the probability to contract a new bank loan, and on the amount of this loan. We estimate the following specification:

$$BkL_{i,t} = \alpha_1 PI_{i,t-1} + \alpha_2 PI_{i,t-2} + \beta_j X_{i,t-1} + \mu_t + \rho_i + \epsilon_{i,t} \quad (5)$$

where $BkL_{i,t} \geq 0$ represents the amount of new bank loans contracted by firm i during year t, $PI_{i,t-1}$ is a binary variable equal to 1 whenever firm i had a payment incident during year $t-1$, and $X_{i,t-1}$ is a set of controls that includes various determinants of bank loans supply. In particular, we control for firm size (number of employees) and its squared value, for the firm's cash-flow, and for collateral and the firm's dependence upon bank finance (banking debt over total debt)[7]. All these variables are

[7]A more detailed description of the computation of these different variables is provided in the Appendix - Table 13.

lagged.

We expect the supply of bank loans to be higher for firms with higher cash flow and collateral. Size may have a non-linear effect - i.e. a lower positive effect on credit supply at higher levels. Finally, we expect the estimated coefficients on the PI variable to be negative - banks are supposed to reduce their credit supply to firms that failed to repay their trade creditors.

We also include a full set of year dummies (μ_t) to account for time specific effects, and estimate the equation with firms' fixed effects (ρ_i). Alternatively, we assess separately the impact of having experienced a payment incident in the past, on both, the access to new bank loans (by using a Logit estimation) and on the amount of this loan (by using a left-censored, Tobit estimation). Finally, we replace the dependent variable "new bank loans" by the share of long term loans over total loans. The idea here is that credit constrained firms have relatively more short term loans as banks are more reluctant to give them long terms ones. We thus expect the coefficient on PI to be negative in this latter estimation.

Our specification only takes into account supply factors in explaining firms' new bank loans'. However, our regressors may be correlated with factors which affect firms' demand for new loans. In particular, the demand for credit should be positively correlated with firms' investment demand, which itself should be positively correlated with current sales. To partly capture this demand effect, we introduce lagged sales variation, and the lag of the share of R&D investment over value added as additional controls.

[Table 4 about here]

Results are shown in Table 4. The estimated coefficients on control variables have the expected sign: a larger cash flow, size and collateral are all positively correlated with banks credit supply (columns (a) to (d)). Results are qualitatively unchanged when controlling for past sales variations (columns (i) and (j)). Having experienced a payment incident during the previous year has a negative and significant impact, both on the probability to contract a new loan (logit estimation, column (l)) and on the size of the loan (within estimations). In the last two columns we decompose the marginal effects computed from a left-censored tobit estimation of the previous specification in two subcomponents: namely, the marginal effect on the probability to contract a new loan and the effect on the size of the loan. Having experienced a payment incident has more negative impact both on the size of the loan than on the probability to contract a new loan. We also find that having experienced a payment incident two years before does not have any impact on credit supply[8]. One potential explanation for this latter finding

[8]We also tried to determine whether the number of payment incidents or the extent of the unpaid trade credits play

is that the electronic service provided by the Bank of France gives commercial banks access to only the past year PI. Note that the introduction of the convivial internet access in 2000 does not seem to have modified the correlation between PI and credit supply between before and after 2000 (columns (f) and (g)). Finally, our results exhibit a negative correlation between PI and the share of long-term debt in total debt - an especially important fact since we will study in the next part the effect of credit constraints on the share of long-run investment.

These findings are consistent with the idea of a significant impact of payment incidents on credit supply. We shall build on these results in our main analysis, in which we use the binary variable equal to 1 whenever the firm has experienced at least one PI in year $t-1$, as our indicator for credit constraint in year t.

As we explain in more details in the next section, this measure of credit constraint is not immune from potential endogeneity problems. In particular, both the composition of investment and the fact of having experienced a payment incident, may result from the existence of omitted variables. For example the firm may decide that a given activity is no longer worth pursuing, and as a result reduce both, its R&D investment and also its diligence vis-a-vis trade creditors in that activity. To deal with the endogeneity problem and further confirm the relevance of payment incidents as a generator of credit constraints, we use the Rajan and Zingales (1998)'s industry-level measure of financial external dependence[9]. More precisely, we shall run our main estimations on two different sub-samples, respectively containing highly and lowly dependent sectors. We explain our methodology in more details in the next section.

IV Credit constraints and the cyclicality of R&D investment

In this section we use our PI measure of credit constraints to test our main theoretical predictions. In particular we will show that: (1) the R&D / investment ratio is less countercyclical for firms facing tighter credit constraints; (2) this procyclicality effect tends to be asymmetric: it operates mainly during low sales states. The next section will discuss robustness checks and implications of our results, in particular for the effect of volatility on the level of R&D and on average productivity growth in credit-constrained firms.

a role; we find that payment incidents have nearly the same effects on R&D share over the business cycle no matter the number or magnitude of incidents.

[9]See Rajan and Zingales (1998). The RZ indicator measures the extent to which the corresponding sector in the US is more or less dependent upon external finance.

1 Proposition 1: Cyclicality of the R&D share and credit constraints

1.1 Specification

We test our first proposition by estimating the following specification:

$$\frac{RD_{i,t}}{I_{i,t} + RD_{i,t}} = \alpha_0 + \beta_1 \Delta s_{i,t} + \beta_2 \Delta s_{i,t-1} + \beta_3 \Delta s_{it-2} + \theta PI_{i,t-1} +$$

$$\gamma_1 \Delta s_{i,t} * PI_{i,t-1} + \gamma_2 \Delta s_{i,t-1} * PI_{i,t-1} + \gamma_3 \Delta s_{i,t-2} * PI_{i,t-1} + \mu_t + \nu_i + \varepsilon_{it} \quad (6)$$

where RD_{it} represents R&D investment (used as a proxy for long-term, productivity enhancing investment), $I_{i,t} + RD_{i,t}$ total investment (physical plus R&D investment), $PI_{i,t-1}$ the payment incident dummy (used as an indicator for credit constraints), and Δs_{it} the variation in sales[10] of firm i during year t. We control for time fixed effects μ_t[11], and for firms fixed effects.

We thus analyze the interacted impact of sales cycles and credit constraints on the *composition* of investment. Based on our theoretical analysis, we expect the share of R&D investment to be countercyclical in the absence of credit constraints; we thus expect $\beta_1 < 0$ and $\sum \beta_i < 0$. However, credit constraints are supposed to reverse the *cyclicality* of investment composition: they should lead to a less countercyclical long-run investment ($\gamma_1 > 0$, $\sum \gamma_i > 0$). Finally, by themselves credit constraints have an uncertain effect on investment composition. A firm most probably reduces its short- and long-run investment when it is credit constrained; but we do not know which investment will be more affected. Thus, we do not expect a particular sign or significance on θ.

As mentioned before, we estimate the equation with firm fixed effects. The results are almost unchanged when using a Random effects / GLS methodology with sector and size dummies.[12] More importantly, taking into account the important share of zero-values in our R&D variable by estimating the previous specification using a left-censored Tobit does not change the results qualitatively either.

However, the estimated coefficients may be biased since current sales and investment may be co-determined. A traditional solution to this problem is to use an instrumental variable (IV) methodology, where the instruments are an appropriated set of lagged values of the variables. This argues in favor of using the GMM method. Using GMM estimations does not alter the results, both qualitatively and quantitatively[13], but instruments are rejected by the Sargan test of over-identifying restrictions. This

[10] Defined as: $Log(Sales_t) - Log(Sales_{t-1})$.

[11] We also included year×sector dummies to account for sectoral shocks such as privatization. Results were unaffected.

[12] The inclusion of these controls in a within estimation does not add much since sectors and size specific effects are already captured by the firms' fixed effects.

[13] Results available upon request.

is in line with a number of papers including Mulkay *et al.* (2001), which emphasize the weakness of GMM instruments in this kind of firm-level estimations. To account for this potential simultaneity bias, we instead perform two-stage estimations, using two different instrumental variables for current sales variations. We make use of destination-specific information on firms' export quantities (a detailed description of this data is given in appendix) to construct two different indicators, respectively reflecting the level of exchange rate and foreign demand faced by exporters. More precisely, we construct the following indicators:

$$RER_{it} = \Big(\sum_{j=1}^{N} rer_{jt} \times \alpha_{ijt}\Big) \times \frac{X_{i,t-1}}{S_{i,t-1}} \qquad GDP_{it} = \Big(\sum_{j=1}^{N} gdp_{jt} \times \alpha_{ijt}\Big) \times \frac{X_{i,t-1}}{S_{i,t-1}} \tag{7}$$

where rer_{jt} is the real bilateral exchange rate between France and country j, gdp_{jt} is the GDP of country j, α_{ijt} is the share of firm i's total export to country j, X_{it} and S_{it} are firm i's total exports and total sales during year t. For each indicator, the first term represents the average real exchange rate and the average foreign demand faced by a firm i, weighted by the share of each destination in firm i's total exports. The second term represents the firm i's foreign orientation in $t-1$. Both a depreciation (increase in rer) and an increase in foreign demand (increase in gdp) have a positive impact on exports, and then affect positively current sales, especially when the firm is outward oriented. These instruments are firm-year specific, but exchange rate and GDP are determined at the macro level, so that they are fully exogenous to firm-level behavior - in particular to physical investment and R&D patterns. We use the current values and two lags of these two indicators as instruments. We check their validity using the Sargan test of over-identifying restrictions. The Durbin-Wu-Hausman test provides a diagnosis on endogeneity.

1.2 Results

Columns (a), (b) and (c) in Table 5 report the within estimations of the potential impact of sales changes on the composition of investment. These estimations include current sales shocks and up to two-period lagged shocks.

These first results show a countercyclicality of the share of R&D in the investment spending. A 10 percent change in current sales induces a modification in the opposite direction of the share of R&D of 0,2 percentage point the same year, and also the next year, and still half of this effect two years after. But the correlation vanishes for older shocks (regressions not reported). The magnitude of the current impact of this 10 percent change in current sales is quite important: about 4 % of the R&D average share.

[Table 5 about here]

Introducing PI as an additional explanatory variable does not also alter the countercyclicality of the share of R&D in the investment spending. On its own, PI shows no significant impact on the R&D share in the within estimation, suggesting that R&D investment and physical investment tend to be affected in the same way by the occurrence of payment incidents.

Now, when we interact PI with our sales shock variables, we obtain the expected results: consistent with theoretical predictions, the share of R&D investment turns less countercyclical in presence of credit constraints (Table 5, columns (d), (e) and (f)).

Columns (g), (h) and (i) present the results of the two-stage estimations. The sample is reduced because of data availability: we only have destination-specific export information from 1996 to 2004 (due to the use of lagged values of instrumental variables, the time period used in the estimation is then 1998-2004). Running the within estimations on this subsample does not modify the results. Endogeneity cannot be rejected by the Durbin-Wu-Hausman test, but the Sargan test supports the choice of our instruments. The results are slightly different in those specifications: the payment incident variable turns out to be negative and significant, while the variation in sales becomes insignificant. This suggest that the negative relationship between sales' variation and the share of R&D investment found previously was mainly due to the simultaneity between sales and investment. However, our main results are strengthened by the use of instrumental variables: the interaction terms between sales and payment incident are highly significant in t and $t-1$, suggesting that the share of R&D investment turns procyclical in presence of credit constraints.

1.3 Robustness

As already mentioned in the previous section, another source of endogeneity lies in the possibility that both, a firm's investment structure and whether it is subject to a payment incident, may hinge on some omitted variable. Note that the omitted variables have to be firm-year specific (if not, it is captured by year or firm fixed effects), and to co-determine PI in year $t-1$ and the R&D share of investment in year t, without affecting the R&D share at $t-1$ in the same way as it affects the R&D share at t (since the inclusion of a lagged term of the dependant variable does not modify the results). These variables cannot be sector-year specific since the inclusion of sector-year dummies leaves the results unchanged.

To deal with this potential endogeneity problem, we use the sectoral financial dependence indicator of Rajan and Zingales (1998). More precisely, we run the last set of estimations on two different subsamples, respectively consisting of sectors with analogs in the US that are more (above median) and less (below median) financially dependent. Our idea is here twofold. First, there is *a priori* no reason for this endogeneity bias to be differently distributed across sectors with different levels of external dependence, that is, for the omitted variable to affect PI(t-1) and the structure of investment in year t (with the above restrictions) only in sectors that are more dependent upon external finance. Second, the previous results should be exacerbated in more financially dependent sectors. Hence, getting more significant results on the financially dependent sub-sample would suggest both that the endogeneity bias is weak and that payment incident indeed generates firm-level credit constraints. Importantly, the probability of experiencing a payment incident is not correlated with the sectoral degree of financial external dependence: this probability is equal to 7% in both subsamples.

We repeat this robustness check by using the Braun (2003) index of asset tangibility instead of the measure of external dependence. Firms operating in industries characterized by a higher level of asset tangibility[14] are expected to face lower credit constraints, everything else being equal. The interaction between sales and payment incident is thus expected to be more significant for firms operating in industries characterized by a lower level of asset tangibility.

[Table 6 about here]

Results provided in table 6 show that the share of R&D investment becomes less countercyclical in presence of credit constraint only for firms in sectors that are more dependent upon external finance (column (b)). Estimated coefficients are insignificant for firms the other sub-samples (column (a)). This in turn suggests a causal effect of credit constraints on the procyclicality of R&D investments. The two stage estimations confirms those results: R&D turns procyclical in presence of payment incidents only in more financially dependent sectors (column (c) and (d)).

Note that that without credit constraints, the cyclicality of R&D share is not different in the two subsamples (i.e. the coefficient on sales variations statistically different in columns (a) and (b), or (c) and (d)). This suggests that financially dependent sectors are not characterized by a lower level of creative destruction than sectors which do not rely on external finance. This support the validity of our subsample analysis.

These results are confirmed when we divide our sample according to the sectoral degree of asset tangibility (columns (e) to (h)). The interaction between sales and payment incident is strongly significant only in sectors with low asset tangibility (columns (e) and (g)).

[14] Tangible assets include net property, plant and equipment. For more information on the computations of asset tangibility and external dependence indexes, see Braun (2003) and Rajan and Zingales (1998)

2 Proposition 2: Asymmetry between positive and negative shocks

2.1 Specification

The interactions terms in the previous tables need to be interpreted with caution: their positive signs can either mean that credit constraints prevent firms from increasing their R&D share in downturns, or that firms increase more this share during upturns periods when they are financially constrained.

In this section, we disentangle the up- and downturns effects and show that the effect of credit constraints on the R&D share depends upon the firm's position within its business cycle. Intuitively, one expects this effect to be stronger during downturns as credit constraints are more likely to be binding in that case. More specifically, we decompose the sales variation variable in two components: downturns (first quartile of sales variations) and upturns (last quartile). We implicitly assume that a large negative shock leads to the equivalent of our $\underline{a}$ whereas a large positive shock leads to the equivalent of our $\overline{a}$.

We expect credit constraints to prevent firms from increasing their R&D share mainly during downturns, thus it is the interaction terms between this variable and payments incidents that should be most positive and significant. The specification becomes:

$$\frac{RD_{i,t}}{I_{i,t}+RD_{i,t}} = \alpha_0 + \sum_{j=0}^{2}\left(\alpha_j \Delta s^H_{i,t-j} + \gamma_j \Delta s^L_{i,t-j}\right) + \alpha_4 PI_{i,t-1} +$$

$$\sum_{j=0}^{2}\left(\theta_j \Delta s^H_{i,t-j} * PI_{i,t-1} + \lambda_j \Delta s^L_{i,t-j} * PI_{i,t-1}\right) + \mu_t + \nu_i + \varepsilon_{it} \tag{8}$$

where $\Delta s^H_{i,t}$ equals sales variations if the firm is above its mean value for this variable, and to 0 otherwise; $\Delta s^L_{i,t}$ equals sales variations if the firm is below its mean, 0 otherwise. We also use another decomposition of sales shocks, by sector: in this case, $\Delta s^H_{i,t}$ equals sales variations if the firm is above the third quartile (computed by sector) of this variable and zero otherwise; similarly $\Delta s^L_{i,t}$ equals sales variations if the firm below the first quartile, and zero otherwise[15].

Our contention is that credit constraints should play a more important role during recessions ($\lambda_j > 0$, $\lambda_j > \theta_j$).

[15] We also tried with alternative decompositions, based on quartiles computed by year, of sector-year. The results were qualitatively unchanged.

2.2 Results

[Table 7 about here]

Results are provided in table 7. In particular we see that the interaction term between sales variation and PI is significant only for lower shocks. Furthermore, the share of R&D investment turns procyclical[16] for the lower shocks in case of a PI while it is countercyclical when no PI occurs. A 10 percent drop in current sales in a firm experiencing a PI in the previous year, induces a significant reduction of the share of R&D in total investment of about 0.25 point (5%), but for a firm that has not experienced PI this share falls down to 3%. Finally, whether firms are subject to PI or not, the share of R&D in total investment becomes countercyclical for large positive sales shocks. This is consistent with the view that firms escape their credit constraints thanks to upward positions in their business cycle. Note also that the uninteracted effect of PI is not affected by the decomposition. Finally, the use of IV methodology confirms that the interacted term between payment incidents and sales variations is only significant for low sales shocks (columns (e), (f), (k) and (l)).

3 Shock and cyclical position of the firm

One objection to the previous estimation relates to the implicit assumption that the size of shocks determines the position of the firm within its business cycle. However, even if firms are in the low (resp. high) part of their business cycle they may experience large negative (resp. positive) shocks.

To handle this caveat, we divide our sample according to the initial position of firms. We assume that a firm is already lying on the upward (resp. downward) part of its cycle if the real sales per employee are above (resp. below) its median.

- When a firm lies initially in the upward part of its cycle at time $t-1$, we expect: (i) that the effect of a high sales shock alone should be either negative (the share of R&D investment becomes more countercyclical as the firm moves further up) or insignificant (as the share of R&D investment is low from the start); (ii) that the effect of a payment incident on the R&D share is insignificant as the credit constraint is essentially not binding; (iii) that a low sales shock should significantly increase the share of R&D; (iv) finally, that the interaction effect between PI and a (small) sales shock should not be significant.

[16]This procyclicality is confirmed by a Wald test, showing that the coefficient on Δs_t is significantly lower than the coefficient on $\Delta s_t * PI(t-1)$.

- When a firm lies initially in the downward part of its cycle at $t-1$, the interaction between PI and a positive sales shock should become positive and significant.

[Table 8 about here]

Results in Table 8 are consistent with these predictions and our previous estimations. Whatever the initial position of the firm, the correlation between a sales shock and the R&D share is, as expected, non positive for firms without PI and non negative for firms affected by a PI. In addition, if the initial position of the firm is high, the coefficients are significantly different from zero when the sales shock is adverse. Alternatively, if the initial position of the firm is low, the coefficients are significantly different from zero when the sales shock is positive.

V Discussion

In this section we discuss some extensions and implications of our analysis. First, we argue that our main results carry over when we move from R&D *share* of investment to R&D *levels*: in other words, the higher procyclicality of the R&D share in a more credit-constrained firm, is not primarily driven by a variation in its physical investment. Second, we weight our estimations by the size of the firm to check that our micro results hold at a macro level. Finally, move from R&D share to firm level productivity growth and analyze how this latter variable responds to sales volatility interacted with firm-level credit constraints.

1 From R&D share to R&D level

As total investments are not constant over the firm's business cycle, our previous results do not provide direct information on how the average *level* of R&D investment is affected by credit constraints. For example, a procyclical R&D share would be consistent with the level of R&D either increasing or decreasing, if it turned out that the amount of physical invesment increases sufficiently during slumps.

The easyest way to tackle this issue would have been to use the accumulation rate of R&D as the left hand side variable in our regressions. However, the computation of R&D capital stock is subject to many technical problems which prevent the results from being easily interpreted. Another way to answer the question is then to look at the accumulation rate of physical investment, and derive from its variations and from our results on the share of R&D investment the impact of credit constraints on the level of R&D. We then chose to present both the results on the R&D and physical investment levels.

We use the following specification:

$$\frac{Inv_{i,t}}{K_{i,t-1}} = \alpha_0 + \eta_1 \frac{Inv_{i,t-1}}{K_{i,t-2}} + \xi_1 \Delta s_{i,t} + \xi_2 \Delta s_{i,t-1} + \alpha_1 PI_{i,t-1} + \beta_1 \Delta s_{i,t} * PI_{i,t-1} + \beta_2 \Delta s_{i,t-1} * PI_{i,t-1} + \mu_t + \nu_i + \varepsilon_{it} \quad (9)$$

where $Inv_{i,t}$ is either physical investment or R&D investment, $K_{i,t}$ denotes either the stock of capital or the stock of R&D, and $\Delta s_{i,t}$ is the variation in sales of firm i during year t. The dependent variable is the accumulation rate of either physical capital or R&D. We estimate this equation with firms and year fixed effects[17].

We expect both physical investment and R&D investment to be procyclical ($\xi_1, \xi_2 > 0$) and negatively affected by credit constraints ($\alpha_1 < 0$). The signs of β_1 and β_2 provide direct information on the cyclical variation of both physical investment and R&D in response to credit constraints. The latter are supposed to influence the cyclicality of R&D investment without affecting the cyclical behavior of short-run investment. We thus expect β_1 and β_2 to be significantly positive when estimating the above equation using R&D investment as a dependent variable, while those coefficients are expected to be insignificant on physical investment.

[Table 9 about here]

Our results are in line with these predictions. Table 9 shows that both R&D and physical investment are procyclical. Consistently with theory, R&D is less procyclical. Payment incident affects negatively both R&D and physical investment. More importantly, physical investments are uniformly affected by credit constraint over the business cycle (column (f)), whereas R&D level turns more procyclical when the firm has experienced a payment incident (column (c)). This, together with our previous findings, makes it clear that: (a) the average level of R&D investment decreases with sales volatility when the firm is more credit constrained; (b) this level decreases more in downturns for more credit-constrained firms.

[17] We also have estimated the effect of PI and its interaction with Δs_t using structural investment equations based on Mulkay *et al.* (2001). The results, available upon request, were qualitatively unchanged.

2 From micro to macro effects of credit constraints

If our results are significant at the individual level, one may argue that innovative behavior over the cycle should not be affected by credit constraints at the macro level. Indeed, most of R&D investment is concentrated on a few large firms, which are less likely to be hit by credit constraints. Moreover, as our previous estimates treat each firm as one observation, regardless of their size, our results may only suggest that, although significant at the individual level, the effect we find leaves overall R&D roughly unaffected.

In this section, we check the robustness of our results at the macroeconomic level. More precisely, we weight our estimations by the size of the firm (either value added or number of employees). In such estimation, a firm employing ten workers will be accounted ten times. Results are reported in table 10.

[Table 10 about here]

As exposed in Table 10, R&D is still significantly more procyclical in credit constrained firms than in firms which did not experienced a payment incident in $t-1$. Even when weighting the estimations by firms size, the interaction terms between PI and variation in sales remain significant - even if lower in value in columns (a) and (b). Only the payment incidents variable becomes positive and significant (only at ten percents in estimation (d)), suggesting that large firms, when facing such an incident, decrease more their short-run physical investment than their long-run, R&D investment than small firms.

Thus, our main results should be significant even at the macro level. Moreover, another important effect, dynamic, cannot be captured by the present estimations, but should be added to the overall effect of credit constraints and business cycles on innovation and growth at the macro level: by preventing small firms to make their innovation in downturns, credit constraints may also prevent those firms from growing. This mechanism, which is not taken into account in these weighted estimations, may also affect negatively overall growth, as well as overall R&D investment.

3 From R&D to productivity growth

In this subsection we investigate the interacted effect of PI and sales shocks on firm average productivity growth. The prediction is that the interacted effect should be negative, with growth in more credit constrained firms responding more positively to a positive sales shock.

[Table 11 about here]

Results in Table 11 are in line with these predictions. First, the effect of adverse shocks on average productivity growth for credit constrained firms is negative: the variable shock in this table is a dummy equal to 1 when the firm has experienced both, an adverse shock and a payment incident in year $t-1$. The table shows an estimated coefficient of average productivity growth on this variable which is negative and significant. When we control for sectoral R&D intensity (captured by the mean of the share of R&D investment over total investment, computed by sector), this coefficient is no longer significant, whereas the interaction term remains negative and significant. This suggests that the negative effect of adverse shocks on productivity growth in credit constrained firms is related to the impact of those shocks on long-term R&D investment.

[Table 12 about here]

Additional evidence on the role of credit constraints in the relationship between business cycles and productivity growth is presented in table 12, which presents cross-section estimations of the correlation between the volatility of growth and average TFP growth over the period 1994-2004. All estimations include controls for firm size and sector dummies. The impact of growth volatility alone is found to be insignificant (column (a)), but turns negative in more financially dependent industries (column (b)). In the last four columns we present separate estimations for high (above median) and low (below median) R&D intensity sectors. Consistent with our theoretical model, the negative impact of volatility on growth in more financially dependent sectors appears only in R&D intensive industries, suggesting that credit constraints magnify the negative impact of volatility on growth at least partly through their effects on R&D investment. Finally, those conclusions hold at the macro level too: the consideration of estimations weighted by firms' size does not alter the results of tables 11 and 12.[18]

Conclusion

In this paper, we analyse the relationship between credit constraints and firms' R&D behavior over the business cycle using a French firm-level panel data set over the period 1993-2004. We show that: (i) the share of R&D investment over total investment is countercyclical without credit constraints, but it becomes less countercyclical as firms face tighter credit constraints; (ii) the result is magnified for firms in financial dependent sectors, and in sectors characterized by a low degree of asset tangibility; (iii) in more credit constrained firms, R&D investment share plummets during recessions but does not increase proportionally during upturns; (iv) average R&D investment and productivity growth are more negatively correlated with sales volatility in more credit constrained firms.

[18]Results available upon request.

An important next step in this research program will be to study the effect of macro-policy - both monetary and budgetary policies - on firms' R&D behavior over the business cycle. In particular, our regression results in Tables 6, 11 and 12 suggest that more countercyclical macroeconomic policies (e.g with higher fiscal deficits or lower interest rates in downturns) should enhance R&D investments and productivity growth in firms that are more credit constrained and more dependent upon external finance. However, a systematic investigation of the effects of macroeconomic policies on firms' investment behavior is left for future research.

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Tables

Table 1: Descriptive Statistics, whole sample

Variable	No Obs.	No. Firms	Mean	S.D	Q1	Median	Q3
Whole Sample							
No Employees	73,237	12,966	94.70	288.03	16	32	68
Sales (1)	73,237	12,966	21141	1.9e+05	2098	4417	11126
Variation in Sales	73,237	12,966	0.04	0.19	-0.05	0.04	0.13
Payment Incidents (PI)	73,237	12,966	0.07	0.26	0.00	0.00	0.00
R&D Share (2)	73,237	12,966	0.05	0.14	0.00	0.00	0.00
Credit Constrained Firms (4)							
No Employees	26,864	4,646	110.86	331.63	17.00	34.00	72.00
Sales (1)	26,864	4,646	24512	1.9e+05	1919	4113	10549
Variation in Sales	26,864	4,646	0.04	0.19	-0.05	0.04	0.13
Payment Incidents	26,864	4,646	0.20	0.40	0.00	0.00	0.00
R&D Share (4)	26,864	4,646	0.04	0.15	0.00	0.00	0.00
Non Credit Constrained Firms (5)							
No employees	46,373	8,320	85.33	258.98	16.00	31.00	66.00
Sales (1)	46,373	8,320	19189	1.8e+05	2210	4589	11454
Variation in Sales	46,373	8,320	0.05	0.19	-0.04	0.04	0.13
R&D Share (4)	46,373	8,320	0.05	0.14	0.00	0.00	0.00
Payment incident							
No employees	51,656	11,392	98.30	292.25	17.00	34.00	72.00
New Bank Loans / VA	54,253	11,392	0.03	1.37	0.00	0.00	0.01
Long Term / Total Loans	54,572	11,367	0.39	0.38	0.00	0.27	0.77
Collateral (1)	51,656	11,392	15784	1.8e+05	688	1716	4939
Bank Debt / Total Financing	51,651	11,390	0.22	0.20	0.05	0.17	0.33

Note: (1) : Thousands of euros; (2) R&D share : R&D investment / (Physical Investment + R&D Investment); (3) Capital Stock Growth Rate : I_t/K_{t-1}; (4): At least 1 payment incident during the period; (5) no payment incident during the period; Positive R&D investment rate for 24% of the total number of observations. Source: Authors' computations from Fiben / Centrale des Bilans, Banque de France.

Table 2: Descriptive Statistics, by sector

Sector	**N (1)**	**Share (2)**	**No.Empl.** (median)	**No.Empl.** (mean)	**R&D/I** (mean)	**PI**(3)	**CC (4) firms**
Agriculture, forestry, fishing	138	1,06%	20	46	0,02	0,09	0,30
Manuf. of food products, bev., tobacco	642	4,95%	36	102	0,03	0,07	0,33
Manuf. of consumers goods	1045	8,06%	34	100	0,07	0,08	0,35
Manuf. of motor vehicles	204	1,57%	56	212	0,08	0,08	0,41
Manuf. of capital goods	2111	16,28%	32	84	0,11	0,08	0,36
Manuf. of intermediate goods	2503	19,30%	38	92	0,04	0,07	0,35
Energy	67	0,52%	48	374	0,04	0,04	0,19
Construction	618	4,77%	28	56	0,03	0,08	0,37
Trade	2724	20,01%	17	46	0,04	0,07	0,31
Transports	419	3,23%	41	166	0,02	0,05	0,26
Real estate activities	140	1,08%	14	40	0,03	0,03	0,16
Services to businesses	2104	16,23%	21	80	0,12	0,04	0,18
Personal and domestic services	251	1,94%	25	182	0,03	0,07	0,29
Total	**12966**	**100**	**32**	**94,70**	**0,05**	**0,07**	**0,35**

(1) Number of firms (2) Share of the total number of firms (3) Share of observations with a PI (4) Share of credit constrained firms, i.e. share of firms with at least one time one payment incident during the period. Source: Authors' computations from Fiben, Banque de France.

Table 3: Effect of R&D on TFP Growth

Depvar:	Average TFP Growth (t+2 to t+4)			
	(a)	(b)	(c)	(d)
Initial TFP	-0.023[a]		-0.024[a]	
	(0.001)		(0.001)	
R&D investment/VA	0.163[a]	0.074[a]		
	(0.018)	(0.025)		
R&D Invest./ Total Invest.			0.044[a]	0.012[c]
			(0.004)	(0.006)
Obs.	34596	36364	33627	35299
Adj. R^2	0.033	0.025	0.035	0.025
Estimation	OLS	Within	OLS	Within

Note: Panel, within estimation. Robust standard errors into parentheses. Significance levels: [c]10%, [b]5%, [a]1%. All estimations include year dummies. Intercept not reported.

Table 4: Payment Incidents as a generator of Credit Constraints

	WITHIN									WITHIN		LOGIT	TOBIT	
Dep. var. :	New bank loans									Long term loans/ Total loans		New bank loans $P(X>0)$ (Marginal Effects)	$P(X>0)$	$E(X \mid X>0)$
	(a)	(b)	(c)	(d)	(e)	(f) Before 2000	(g) After 2000	(h)	(i)	(j)	(k)	(l)	(m)	(n)
PI(t-1)	-0.264^a	-0.243^a	-0.239^a	-0.238^a	-0.227^a	-0.229^b	-0.256^a	-0.229^a	-0.228^a	-0.021^a	-0.020^a	-0.042^a	-0.043^a	-0.173^a
	(0.038)	(0.040)	(0.040)	(0.040)	(0.042)	(0.110)	(0.053)	(0.043)	(0.043)	(0.003)	(0.003)	(0.007)	(0.007)	(0.028)
PI(t-2)		-0.064	-0.059	-0.068^c	-0.057	-0.185^c	-0.042	-0.062	-0.062		-0.015^a	-0.003	-0.002	-0.008
		(0.041)	(0.041)	(0.041)	(0.042)	(0.112)	(0.051)	(0.045)	(0.045)		(0.003)	(0.008)	(0.007)	(0.030)
Cash-flow(t-1)		0.575^a	0.514^a	0.424^a	0.430^a	0.492^a	0.270^a	0.391^a	0.396^a		0.070^a	0.321^a	0.309^a	1.244^a
		(0.075)	(0.075)	(0.075)	(0.102)	(0.184)	(0.090)	(0.098)	(0.098)		(0.006)	(0.020)	(0.017)	(0.071)
Size(t-1)		0.292^a	0.158^a	0.094	0.006	-0.125	0.080	0.025	0.031		-0.011^c	0.120^a	0.107^a	0.434^a
		(0.107)	(0.107)	(0.111)	(0.101)	(0.358)	(0.168)	(0.137)	(0.137)		(0.006)	(0.009)	(0.007)	(0.029)
Size^2(t-1)		-0.031^c	-0.032^c	-0.023^b	-0.014	0.013	-0.022	-0.017	-0.017		0.000	-0.017^a	-0.014^a	-0.059^a
		(0.017)	(0.017)	(0.017)	(0.015)	(0.051)	(0.027)	(0.021)	(0.021)		(0.001)	(0.001)	(0.001)	(0.003)
Collateral(t-1)			0.288^a	0.327^a	0.324^a	0.315^a	0.346^a	0.340^a	0.333^a		0.010^a	0.012^a	0.017^a	0.068^a
			(0.025)	(0.026)	(0.024)	(0.076)	(0.034)	(0.032)	(0.033)		(0.002)	(0.002)	(0.002)	(0.007)
Bank dep.(t-1)				-1.355^a	-1.378^a	-3.099^a	-1.568^a	-1.340^a	-1.339^a		0.268^a	0.260^a	0.353^a	1.421^a
				(0.138)	(0.127)	(0.378)	(0.181)	(0.150)	(0.150)		(0.008)	(0.017)	(0.015)	(0.059)
ΔSales(t-1)					0.053^c			0.139^a	0.142^a		0.001			
					(0.028)			(0.040)	(0.041)		(0.002)			
ΔSales(t-2)					0.109^a			0.155^a	0.157^a		0.004^b			
					(0.026)			(0.035)	(0.035)		(0.002)			
$R\&D/VA$(t-1)								0.436^c	0.429^b					
								(0.406)	(0.406)					
ΔSales(t)									0.024^a					
									(0.037)					
Obs.	54266	51140	51140	50667	47578	14473	36194	45515	45515	54572	54572	50667	50667	50667
No. Firms	11911	11375	11375	11310	10664	8167	10124	10459	10459	11367	11367	11310	11310	11310
Adjusted R^2	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.04			
Log Likelihood												-29333.02	-63257.82	-63257.82
Year / Sect. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors into parentheses. All variables are computed from Fiben / Centrale des Bilans, Banque de France. PI : Payment Incident (0/1); Bank Dep.: (Banking Debt / Total Debt). Significance levels: ^{c}10%, ^{b}5%, ^{a}1%. Intercept not reported. All variables are in logarithms. Marginal effects computed at means for logit and tobit estimations.

Table 5: Credit constraints and the cyclical composition of investment (1)

Depvar:	*R&D investment / Total Investment*						*R&D inv./Total Inv.*		
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)
Δ*Sales(t)*	-0.016^a	-0.018^a	-0.020^a	-0.018^a	-0.020^a	-0.022^a	-0.002	-0.036	-0.050
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.068)	(0.068)	(0.068)
Δ*Sales(t-1)*		-0.014^a	-0.016^a		-0.015^a	-0.017^a		-0.007	-0.014
		(0.003)	(0.003)		(0.003)	(0.003)		(0.016)	(0.019)
Δ*Sales(t-2)*			-0.010^a			-0.011^a			-0.007
			(0.003)			(0.003)			(0.012)
PI(t-1)				0.003	0.002	0.002	-0.018^a	-0.021^a	-0.018^a
				(0.002)	(0.002)	(0.002)	(0.006)	(0.007)	(0.007)
Δ*Sales(t)*PI(t-1)*				0.029^a	0.030^a	0.030^a	0.687^a	0.655^a	0.533^a
				(0.010)	(0.010)	(0.010)	(0.220)	(0.204)	(0.195)
Δ*Sales(t-1)*PI(t-1)*					0.017	0.018		0.069^a	0.061^a
					(0.011)	(0.011)		(0.019)	(0.018)
Δ*Sales(t-2)*PI(t-1)*						0.013			0.011
						(0.010)			(0.012)
No Obs.				73,237				30,052	
No Groups				12,966				6,587	
Estimation				Within				FE-2SLS	
Sargan Stat.							7.192	6.462	10.525
P-value							0.707	0.775	0.396
Durbin-Wu-Hausman Stat.							11.824	11.25	7.388
P-value							0.003	0.004	0.025

Note: Panel, within estimations. Robust standard errors into parentheses. Significance levels: ^{c}10%, ^{b}5%, ^{a}1%. All estimations include year dummies. Intercept not reported. Current value and two lags of RER_{it} and GDP_{it} used as instruments in columns (g) to (i).

Table 6: Main regressions with financial dependence, asset tangibility

Depvar:	*R&D investment / Total Investment*				*R&D investment / Total Investment*			
	Financial Dependence				Asset Tangibility			
	Low	High	Low	High	Low	High	Low	High
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Δ*Sales(t)*	-0.021[a]	-0.038[a]	-0.027	-0.014	-0.038[a]	-0.022[a]	-0.050	-0.059
	(0.005)	(0.006)	(0.107)	(0.109)	(0.006)	(0.005)	(0.102)	(0.089)
Δ*Sales(t-1)*	-0.012[b]	-0.032[a]	-0.019	-0.013	-0.031[a]	-0.006	-0.027	-0.019
	(0.005)	(0.006)	(0.027)	(0.037)	(0.006)	(0.005)	(0.035)	(0.023)
Δ*Sales(t-2)*	-0.013[a]	-0.027[a]	-0.007	-0.012	-0.026[b]	-0.009[b]	-0.021	-0.013
	(0.005)	(0.006)	(0.018)	(0.027)	(0.005)	(0.004)	(0.024)	(0.018)
PI(t-1)	0.003	0.002	0.006	-0.026[b]	0.003	0.003	-0.019[b]	-0.005
	(0.004)	(0.005)	(0.008)	(0.011)	(0.004)	(0.003)	(0.009)	(0.011)
Δ*Sales(t)*PI(t-1)*	0.026	0.049[b]	-0.013	0.561[c]	0.058[b]	0.036[c]	0.399[c]	0.236
	(0.020)	(0.020)	(0.016)	(0.306)	(0.018)	(0.018)	(0.224)	(0.238)
Δ*Sales(t-1)*PI(t-1)*	-0.001	0.011	0.007	0.138[b]	0.024	-0.020	0.091[a]	0.020
	(0.019)	(0.023)	(0.017)	(0.055)	(0.019)	(0.019)	(0.033)	(0.024)
Δ*Sales(t-2)*PI(t-1)*	0.000	0.049[b]	0.014	0.025	0.044[b]	-0.002	0.045[b]	0.022
	(0.018)	(0.021)	(0.014)	(0.029)	(0.019)	(0.016)	(0.023)	(0.020)
No Observations	20,028	18,457	9,272	8,234	22,892	20,363	10,064	9,436
No Firms	3,403	3,221	2,345	2,485	3,957	3,423	2,853	2,511
Estimation	Within		FE-2SLS		Within		FE-2SLS	
Sargan Stat.			13.285	10.250			17.663	11.693
P-value			0.208	0.419			0.061	0.306
Durbin-Wu-Hausman Stat.			0.085	3.331			2.360	0.709
P-value			0.958	0.189			0.3072	0.701

Note: Panel, within estimations. Robust standard errors into parentheses. Significance levels: [c]10%, [b]5%, [a]1%. All estimations include year dummies. Intercept not reported. Rajan and Zingales (1998) data for sectoral financial dependence. Braun (2003) data for sectoral asset tangibility. Current value and two lags of RER_{it} and GDP_{it} used as instruments in columns (g) to (i).

Table 7: Credit constraints and the cyclical composition of investment, asymmetry, Within estimations (1)

Depvar:	*R&D investment / Total Investment*											
	Decomposition by firm (1)						*Decomposition by Sector (2)*					
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
High Δ*Sales(t)*	-0.020^a	-0.023^a	-0.021^a	-0.023^a	0.046	-0.034	-0.017^a	-0.019^a	-0.018^a	-0.020^a	0.046	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.123)	(0.117)	(0.004)	(0.004)	(0.004)	(0.004)	(0.111)	(0.111)
Low Δ*Sales(t)*	-0.008	-0.011^b	-0.014^b	-0.016^a	0.030	0.066	-0.010^c	-0.013^b	-0.016^a	-0.019^a	-0.052	-0.077
	(0.005)	(0.005)	(0.006)	(0.006)	(0.143)	(0.149)	(0.006)	(0.006)	(0.006)	(0.006)	(0.132)	(0.137)
High Δ*Sales(t-1)*		-0.015^a		-0.017^a		-0.016		-0.013^a		-0.015^a		-0.011
		(0.004)		(0.004)		(0.019)		(0.004)		(0.004)		(0.018)
Low Δ*Sales(t-1)*		-0.012^b		-0.012^b		0.016		-0.013^b		-0.013^b		-0.006
		(0.006)		(0.006)		(0.023)		(0.006)		(0.006)		(0.022)
PI(t-1)			0.003	0.003	0.055^b	0.043^b			0.003	0.003	0.047^b	0.040^b
			(0.003)	(0.003)	(0.022)	(0.020)			(0.002)	(0.003)	(0.021)	(0.020)
High Δ*Sales(t)*PI(t-1)*			0.005	0.005	-0.294	-0.214			0.007	0.005	-0.085	-0.026
			(0.016)	(0.016)	(0.268)	(0.255)			(0.015)	(0.016)	(0.249)	(0.252)
Low Δ*Sales(t)*PI(t-1)*			0.054^a	0.055^a	0.733^a	0.733^a			0.056^a	0.058^a	0.834^a	0.822^a
			(0.017)	(0.017)	(0.186)	(0.204)			(0.017)	(0.017)	(0.255)	(0.267)
High Δ*Sales(t-1)*PI(t-1)*				0.024		0.053				0.024		0.053
				(0.016)		(0.022)				(0.016)		(0.033)
Low Δ*Sales(t-1)*PI(t-1)*				0.005		-0.033				0.001		0.023
				(0.021)		(0.046)				(0.021)		(0.054)
No Obs.			73,237			30,052			73,237			30,052
No Firms			12,966			6,587			12,966			6,587
Estimation			WITHIN			FE-2SLS			WITHIN			FE-2SLS
Sargan Stat.					5.459	5.353					5.599	5.380
P-value					0.707	0.719					0.692	0.716
Durbin-Wu-Haus. Stat.					12.194	10.836					12.391	11.172
P-value					0.0160	0.028					0.015	0.024

Note: (1) Decomposition by firm: above (high) and below (low) firm's mean sales' variation; (2) Decomposition by sector: firm above the third quartile of its sector's sales variation (high) or below the first quartile (low). Panel, within estimations. Robust standard errors into parentheses. Significance levels: ^{c}10%, ^{b}5%, ^{a}1%. All estimations include year dummies. Intercept not reported. Current value and two lags of RER_{it} and GDP_{it} used as instruments in columns (g) to (i).

Table 8: Asymmetry, with initial state

Dep. var.	$R\&D/(I+R\&D)$	
Initial State:	High	Low
Est.	(a)	(b)
High Δ*Sales(t)*	-0.002	-0.025^{a}
	(0.006)	(0.005)
Low Δ*Sales(t)*	-0.018^{a}	-0.027^{a}
	(0.006)	(0.009)
PI(t-1)	0.004	0.003
	(0.003)	(0.003)
High Δ*Sales(t)*PI(t-1)*	0.025	0.007
	(0.024)	(0.018)
Low Δ*Sales(t)*PI(t-1)*	0.042^{b}	0.060^{b}
	(0.020)	(0.025)
No. Obs.	34,360	38,877
No. Firms	11,563	12,597
Estimation	Within	

Note: High resp. low) state: sales per employee above (resp. below) firms' median. Standard errors into parentheses. Significance levels: ^{c}10%, ^{b}5%, ^{a}1%. All estimations include year dummies. Intercept not reported. All variables are in logarithms.

Table 9: Levels of R&D and Physical Investment

Dep. var. Accumulation rate: $\frac{Inv_t}{K_{t-1}}$

	R&D			Physical Investment		
	(a)	(b)	(c)	(d)	(e)	(f)
$Inv(t-1)/K(t-2)$	-0.020^{a}	-0.009^{b}	-0.009^{b}	0.058^{a}	0.058^{a}	0.058^{a}
	(0.004)	(0.004)	(0.008)	(0.008)	(0.008)	(0.008)
Δ*Sales(t)*	0.015^{a}	0.014^{a}	0.010^{b}	0.127^{a}	0.127^{a}	0.126^{a}
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)
Δ*Sales(t-1)*	0.006	0.007	0.002	0.095^{a}	0.095^{a}	0.095^{a}
	(0.005)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)
PI(t-1)		-0.004^{b}	-0.005^{a}		-0.013^{a}	-0.012^{a}
		(0.002)	(0.002)		(0.004)	(0.004)
Δ*Sales(t) * PI(t-1)*			0.047^{a}			0.007
			(0.016)			(0.021)
Δ*Sales(t-1) * PI(t-1)*			0.055^{a}			-0.008
			(0.017)			(0.023)
Adjusted R^2	0.01	0.01	0.01	0.08	0.08	0.08
No Obs.	61,627	61,627	61,627	72,609	72,609	72,609
No Firms	11,520	11,520	11,520	12,877	12,877	12,877
Estimation		Within			Within	

Note: Robust standard errors into parentheses. Significance levels: ^{c}10%, ^{b}5%, ^{a}1%. All estimations include year and sector dummies. Intercept not reported.

Table 10: Credit constraints and the cyclicality of R&D investment, Weighted estimations

Depvar:	*R&D investment / Total Investment*			
	(a)	(b)	(c)	(d)
Δ*Sales(t)*	-0.016^{a}	-0.018^{a}	-0.021^{a}	-0.022^{a}
	(0.000)	(0.000)	(0.001)	(0.001)
Δ*Sales(t-1)*	-0.013^{a}	-0.014^{a}	-0.015^{a}	-0.017^{a}
	(0.000)	(0.000)	(0.001)	(0.001)
Δ*Sales(t-2)*		-0.012^{a}		-0.011^{a}
		(0.000)		(0.001)
PI(t-1)	0.003^{a}	0.002^{a}	0.002^{a}	0.001^{c}
	(0.000)	(0.000)	(0.001)	(0.001)
Δ*Sales(t)*PI(t-1)*	0.002^{a}	0.003^{a}	0.028^{a}	0.028^{a}
	(0.001)	(0.001)	(0.004)	(0.004)
Δ*Sales(t-1)*PI(t-1)*	0.003^{a}	0.005^{a}	0.016^{a}	0.017^{a}
	(0.001)	(0.001)	(0.004)	(0.004)
Δ*Sales(t-2)*PI(t-1)*		0.020^{a}		0.014^{a}
		(0.001)		(0.003)
No Obs.	73,237			
No Groups	12,966			
Estimation	Within			
Weighted by	No. Workers		Value Added	

Note: Panel, weighted least squares. Robust standard errors into parentheses. Significance levels: ^{c}10%, ^{b}5%, ^{a}1%. All estimations include year dummies. Intercept not reported.

Table 11: Productivity, R&D and Credit Constraints

Dep. var.:	MEAN TFP Growth (t+2) to (t+5)			
	(a)	(b)	(c)	(d)
Initial TFP	-0.031^a	-0.031^a		
	(0.001)	(0.001)		
Shock	-0.063^a	-0.017	-0.037^c	0.001
	(0.019)	(0.026)	(0.020)	(0.027)
Sect. R&D Intensity	1.104^a	1.095^a		
	(0.041)	(0.042)		
*Shock*Sect R&D Intensity*		-3.936^a		-3.284^b
		(1.487)		(1.575)
No obs.	33,973	33,973	33,973	33,973
R^2	0.05	0.06	0.05	0.05
Est.	OLS		Fixed Effects / Within	

Note: Robust standard errors into parentheses. Significance levels: ^{c}10%, ^{b}5%, ^{a}1%. All estimations include year dummies. Shock equals 1 if the firm is credit constraint and has a negative shock in t, 0 otherwise. R&D intensity : industry mean of R&D Investment / Total Investment.

Table 12: Volatility, Growth and Credit Constraints

Dep. Var	TFP Growth		TFP Growth High R&D intensity		TFP Growth Low R&D intensity	
	(a)	(b)	(c)	(d)	(e)	(f)
Initial TFP	-0.021^a	-0.020^a	-0.021^a	-0.020^a	-0.022^a	-0.022^a
	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Growth Volatility	0.003	-0.037	-0.012	-0.074^c	0.012	-0.015
	(0.022)	(0.028)	(0.035)	(0.039)	(0.026)	(0.038)
*Growth volatility*Fin. Dep*		-0.033^c		-0.066^c		-0.018
		(0.018)		(0.037)		(0.021)
No. Observations	4459	4459	2249	2249	2310	2310
R^2	0.141	0.146	0.152	0.164	0.089	0.090

Note: Robust standard errors into parentheses. Significance levels: ^{c}10%, ^{b}5%, ^{a}1%. OLS estimations, over the period 1994-2004; each estimation includes sector and size dummies. Rajan and Zingales (1998) data for sectoral financial dependence. R&D intensity : industry mean of R&D Investment / Total Investment. Large (resp. low) R&D intensity: above (resp. below) median of R&D intensity.

Table 13: Variables Description

Variable	Description	Source
New bank loans	Total amount of new bank loans	Centrale des Bilans, Banque de France (BdF)
Payment Incident	1 when the firm experienced at least one payment incident, 0 otherwise	Observatoire des entreprises, BdF
ΔSales	Log(sales)-Log(sales(t-1))	Fiben, BdF
Size	Number of Employees	Fiben, BdF
Collateral	Sum of fixed and tangible assets	Fiben, BdF
Banking Debt	Banking debt / (Own Financing + Market Financing + Financial Debt)	Fiben, BdF
R&D Share	R&D Investment / (Physical + R&D Investment)	Fiben, BdF
Exchange Rate	Real Bilateral Exchange Rate	IMF / Penn World Tables
GDP	GDP	IMF
Exports	Destination-specific export values	Balance of Payments, BdF

Table 14: Correlations

Variable	Var. Sales	PI	Inv. Rate (1)	R&D Inv. Rate (2)	R&D Share (3)
Variation in Sales	1.0000				
Payment Incidents	-0.0416	1.0000			
Investment Rate (1)	0.349	-0.0068	1.0000		
R&D Investment Rate (2)	-0.006	0.0331	0.2137	1.0000	
R&D Share (3)	-0.0041	0.0363	0.0611	0.7697	1.0000

Note: (1) Capital Stock Growth Rate : I_t/K_{t-1} ; (2): R&D Investment / Value Added; (3) R&D share : R&D investment / (Physical Investment + R&D Investment); ; Source: Authors' computations from Fiben / Centrale des Bilans, Banque de France.