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Abstract

Due to fierce competition, firms always seek to improve their competitiveness. For this purpose, firms invest in innovative activities through R&D expenditures. Nevertheless, this type of investment is risky and is not associated with a positive outcome for sure. In other words, R&D investments do not prevent firms from exiting. In our sample, we see that approximately 6% of French firms that invest in R&D are involved in a collective procedure. This paper investigates whether or not the R&D investment impacts firms' survival, using survival analysis with panel data and taking into account the unobserved heterogeneity. We find that business expenditure in R&D has a U-shaped relationship with survival, highlighting the fact that significant amounts need to be invested in those activities to nullify the negative effect. Moreover, we have evidence of heterogeneity across sectors since the thresholds of investment in R&D vary significantly according to the sector's technological intensity.

JEL code: C41, G33, L11, O31

Keywords: Firm Survival, Bankruptcy, R&D, Performances

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1 Introduction

Innovation drives firm survival as long as innovation output is positively correlated with firm performances. However, R&D investments are costly, highly illiquid and high-risk activities since the outcome is uncertain, particularly when the firm operates in a competitive environment. Two cases are possible: i) the outcome path is successful and the investment was worth it because it allows the firm to maintain its competitiveness on the market; ii) the outcome path is unsuccessful giving rise to financial difficulties (particularly when it is repeated) and to the weakening of its position on the market. The example of the Covid-19 vaccine race demonstrates both the crucial step for firms which compete in this sector and the risk of innovative activities. In France, 6.5% of firms surveyed for their R&D activities are involved in a collective procedure, while in the population of French firms, only 1.5% of firms are involved in such procedures.

Different measures of innovation are proposed in the literature such as patents and shares of innovative sales (Crépon et al., 1998, Alam et al., 2022), which represent the outputs of innovation or R&D investments which are the inputs of innovation. Indicators based on patents are constrained by the winner bias, the patent filing and its maintenance. Some firms may stop protecting its patents because of a negative costs-benefits balance. Note that it may be a part of the strategy of the firm not to deposit a patent to avoid drawing the attention of its competitor, and to choose to keep it as an industrial secret. Based on Chinese data, Chen et al. (2022) bring to light that the number of patents is directly related to R&D expenditure disclosures but the latter may be under-estimated in case of insufficient institutional protection and high market competition. To avoid this measurement issue, we predict the R&D expenditures to measure innovation at the firm-level. This indicator has the advantage to be available for larger samples, with a panel dimension.

To understand why firms in distress may take the decision to do (or to continue) innovation investment, we have to refer to the well-known strand of the literature on firm dynamics that is the passive and active learning models. While in the passive learning model developed by Jovanovic (1982), firms base their decision on their inner efficiency, in the active learning model developed by Ericson and Pakes (1995), they base it on the dynamic of their efficiency. This dynamic of efficiency is fueled by innovation, through R&D expenditures. The empirical literature has highlighted the importance of innovations in the performance of firms. Some of the studies highlight the productivity-innovation relationship using productivity level (Crépon et al., 1998, Janz et al., 2003, Mairesse and Jaumandreu, 2005), while other studies focus on productivity growth (Geroski, 1989, Huergo and Jaumandreu, 2004, Duguet, 2006). All these papers conclude that there is a positive relationship between productivity and innovation, which is robust to the period and the country considered. These findings are consistent with the prediction of Ericson and Pakes (1995). The more successful innovations firms make, the more they improve their productivity levels, allowing them to continue to be competitive and to stay on the market.

However, results are mixed in the literature about the relationship between innovation and survival of firms (see in particular Fernandes and Paunov, 2015, Ugur et al., 2016). As a result of the uncertainty this activity yields, the R&D investment can lead to a less efficient outcome than the competitors' ones. Moreover, since innovation is a risky investment, in case of consecutive unsuccessful outcomes, firms may lose competitiveness and become unable to continue their activities to some extent. Nonetheless, because innovations can also improve firms' productivity, R&D may prevent exit by allowing firms to stay competitive. In this case, it can be seen as a way for firms to diversify the products they sell, thus decreasing the risk.

The aim of this paper is to investigate the relationship between firms' R&D investments, performances, and their survival. Our goal is to determine whether the firms' R&D intensity protect the firms from defaulting, or if it leads to accelerate its downfall. We contribute to the literature on firm survival and R&D investment since no consensus emerges from prior studies. From a methodological aspect, we propose an empirical strategy that allows us to tackle multiple issues. First, we do not consider all types of exits (mergers and acquisitions and voluntary exits are excluded), meaning that we only consider firms in accurate financial distress. Second, we use selection models to predict the investment in R&D. Since all firms do not declare their innovation expenditures and the process is not a random one, we take this selection bias into account, following the works which examine the impacts of indirect R&D such as *"Crédit d'Impôt Recherche"* (see among others Ben Hassine et al., 2020). Being well-known that innovation and firms' inner efficiency are tightly entangled, we assess innovation's net firms' performance. Lastly, we use a survival analysis with the panel dimension of the data and introduce a term to tackle unobserved heterogeneity. This more comprehensive approach enables to grasp the real firm-level effect of both innovative activities and inner efficiency.

Our results suggest that R&D intensity has a U-shaped relationship with survival, indicating that the firm survival increases from a certain level of R&D investments. According to our estimates this threshold is large and reachable only by few firms that massively invest in these risky activities. We also find a strong and positive effect of firms efficiency net of innovation activities on their survival. However, contrary to our expectations, we find a negative correlation between firms' efficiency, which is net of R&D expenditures, and innovation investment, pointing towards the need for efficient firms to invest more than their lesser efficient counterpart. Finally, we find that the impact of both innovation investments and inner efficiency net of innovation activities on firms' survival differs greatly depending on the technological level of the industry they belong to.

This paper is organized as follows. First, we review the literature on the relationship between R&D investment and firm survival in Section 2. We describe the databases we use and our empirical strategy in Section 3. Then, in Section 4 we present some descriptive statistics and our results. Section 5 concludes.

2 The relationship between R&D expenditure and survival

Our paper relies on three nexus which link R&D investment (and more widely innovation), firm performances and firm survival. We will review each of them.

2.1 Innovation and firms' performances

The empirical literature about innovative firms is rich, and the main consistent empirical evidence may be summarized in the paper of Klette and Kortum (2004). To sum up their stylized facts, R&D expenditures viewed as the input of innovation intensity (defined as the ratio of R&D expenditures over sales) is independent of firm size, highly skewed and their differences are persistent. The R&D expenditures follow a geometric random walk, meaning that, there is little change over short-time period in firms R&D investments.

One main contribution of innovative activities' studies is the CDM method (Crépon et al., 1998), which tackles both selection bias and simultaneity issues of innovative investments and their outputs, like patents for example. As documented by Broström and Karlsson (2017), many studies use their methodology to treat the selection bias. Those papers focus on the intensive margins, meaning that they primarily focus on the impact of innovations' outputs on productivity rather than on the investments required to innovate. However, as a counterexample, Arqué-Castells and Mohnen (2015) use the CDM framework on Spain data to assess how public subsidies, as a means to smooth the sunk costs due to entering and continuing innovative activities, affect firms' incentive to invest in R&D afterward. They find that the firms are willing to invest when the subsidies are large enough to start these activities and then pursue them. However, these papers only analyze what happens for incumbents firms (intensive margin) without considering the possibility of bankruptcy (market exit) by R&D firms.

Another strand of the literature focuses on the determinants of firms performances. Among them, there are the expenditures in R&D. The total productivity of factors (TFP) which measures firm efficiency is based on quality of inputs, experience, managerial abilities, the environment in which the firm operates (*external factors* and the buyer-supplier relationships as in Bernard et al., 2019), information technology uses in addition to R&D investments.[1] With regard to our question of interest, in Doraszelski and Jaumandreu (2013), the path of firm productivity results from R&D expenditures even if the outcomes are uncertain. Another channel is through product innovation: R&D investments can lead to higher product quality, which in turn improves firm performances (see among others Bartel et al., 2007).

In the same line, Aw et al. (2008) show that exporters are more likely to do R&D since the potential gains of productivity can be spread across more markets. Based on Taiwanese firm-level data, their results indicate that R&D heightens firm productivity and thus increases the profits of exporting which finally increases also the return to R&D expenditures. In addition, export and R&D activities are complement according to Aw et al. (2005). The combination of both decisions enhances firm productivity because of technology transfers from foreign customers. Note that Liu and Qiu (2016) show that the innovation decision of a firm negatively depends on importing intermediate inputs (due to an access to better technologies at a cheaper price thanks to imports). Using Chinese firms-level data from 1998 to 2007, they find that a reduction of tariff encourages imports of high-quality intermediate and reduce innovative activities. Importing the innovation can prevent firms with low innovation skills and/or high risk aversion from having negative outcomes of R&D.

We will test the following assumption:

H1) Firm's efficiency and innovation investments are positively correlated.

[1] See Syverson (2011) for a complete review of literature on all determinants.

2.2 Performances and exit

In the literature, firms' performances and survival are tightly entangled, with two theoretical models to explain the decision of exiting a market. The first one, the passive learning model explained in the paper of Jovanovic (1982), states that firms' inner performances are key to survive. However, since this efficiency is idiosyncratic, it is both unobservable ex-ante and imperfectly observable ex-post. Thus, after producing for a period of time, firms learn their inner productivity, and if it turns out that they are not sufficiently competitive in the market, they exit. In these models, firms do not have the opportunity to change their efficiency. The second one is the active learning model of firms performances of Ericson and Pakes (1995). In this paper, they formalized the fact that firms can act on their own performances. The model being dynamic, the initial level of efficiency is less important than its dynamic. If the firm cannot improve its performance at the same pace than its competitor, then this firm becomes one of the least performing firms and becomes unable to maintain its position in the market. R&D investments are the perfect example of firms' actions seeking to increase their efficiency and/or their product range in order to improve the firm performances and to stay in the game. We will mainly focus on the active learning approach.

In the empirical literature, firms performances are a well-known factor of survival. In the seminal paper of Griliches and Regev (1995), with the shadow of death model, they found a negative impact of productivity on the exit of Israeli firms. This finding is consistent over time and across countries. Bellone et al. (2006) also find a robust relation between efficiency and failure, both static and dynamic. The dynamic and the level at the time of default are both important. On the other hand, Kiyota and Takizawa (2007) while finding evidence of the relation between firms' productivity dynamics and survival, also conclude that there is no proof of sudden death of firms.
We will test the following hypothesis:

H2) Higher firm efficiency raises the survival probability.

2.3 Innovation and exit

Since the papers using the CDM framework mainly use CIS database (the European surveys on firms' innovation activities), which contains only incumbents and cannot be used as a panel database, they cannot take into account the inherent risk of this activity, as presented by Ericson and Pakes (1995). In the case of the winner-takes-all competition (see for instance Loury, 1979, Lee and Wilde, 1980), the first to achieve the innovation will take, if not all, the largest market share, thus the sales due to this (or these) innovation(s). The rest of firms will only pick-up the crumb, no matter how much they invested in the project. Even if the reality can be less extreme, the first mover have a higher return on its innovation. In addition, focusing only on outputs result in only focusing on successful outcomes of the innovation, because other outcomes are not observable, there is a possibility of survivorship bias. The reason being that, if the loss of the firms are too big, or too frequent, they might be at the end of the pack and be forced to exit.

In the literature about outcome of innovation and survival, the results are mixed. Fernandes and Paunov (2015) examine the relationship between innovation and plant survival. Innovation exposes to higher risk and thus to a higher probability of exit. In their analysis, the risk is measured as the diversification of sources of revenue; the technical risk due to the production of new products; the market uncertainty. Based on discrete-time hazard models, their results suggest that product innovation and the introduction of several products limits the probability of plant death. Innovation is even more valuable when the new product is exported and for firms making investment or importing input (higher productive efficiency). In addition, the first (lack of diversification) and the third one (market risk) are significant while the second one (the proximity of new production to past production) is not. Thus innovative single-plant firms are more likely to die compare to other firms (non-innovative firms and multi-products ones).

In their paper Eisdorfer and Hsu (2011) test and validate three hypothesis from firm-level patent data. First the level of a firm's technology competitiveness predicts its likelihood to fail. They state that financial ratios are not sufficient to capture the situation of a firm and its technology competitiveness is then a better measure. Second, the relation between bankruptcy and macroeconomic conditions is weaker for high technology sectors. Last, bankruptcy of firms in high technology sectors are more costly, which is due to the higher depreciation of the goods produced the inventories and the intermediate inputs used for the producing process.

Considering the sectoral heterogeneity, Sueyoshi and Goto (2009), using data on machinery and electric equipment industries find mixed results of R&D expenditures on financial performances. While the effect is positive for machinery industry, for electric equipment industry the effect is negative. They explain their results by the different products life cycles and the product development paces. The changes in the electric equipment industry is faster than the other one. Because it is a lesser mature industry, the electric equipment sector is associated with high risk but potentially high return innovative investment, while the machinery sector is a more mature industry, so the investments contain less risks but also lower returns.

Ugur et al. (2016) estimate an unshared frailty duration model with and without left truncation, which provides evidence of an inverted-U pattern between innovative activities (i.e. R&D and new products) and survival rates. The market concentration leads innovative firms to survive even longer. Moreover, the authors find evidence that the creative destruction (measured by R&D intensity of the industry) process is negatively correlated with survival time. Finally, the characteristics of the firm are essential since small and young firms, which are the most exposed to the risk of failure, seem to benefit even more from outcomes of R&D investments to survive (Cefis and Marsili, 2006). This result is even stronger on the long run.

We need also to mention the export decision in this nexus. R&D expenditures through innovations at the product and process level impact positively the probability of export as long as the benefits outweigh the costs of innovation.[2] The R&D expenditures-firms' export survival nexus is directly related to the firms' survival question. A substitution relationship does exist between external cooperation and internal innovation particularly when innovative activities rely on the foreign external knowledge stock (see Luh et al., 2016). However, Zhang et al. (2018) demonstrate that knowledge spillovers increase firm survival. Indeed, import and export-related spillovers affect positively firm productivity due to the dissem-

[2]Among others see Dai et al. (2020); Van Beveren and Vandenbussche (2010); Damijan and Kostevc (2015); Altomonte et al. (2013).

ination of information and foreign knowledge. The combination of innovation efficiency (measured by patents) and the internationalization of the firm reduces the firm exit.
We will test the following hypotheses:

H3-a) High level of investments in innovative activities lower the bankruptcy event probability, thus increases the firms' survival probability.

H3-b) The intensity of this effect should be positively correlated with the technology intensity of the sector.

3 Empirical strategy

3.1 Data

We will estimate the impact of business expenditures on research and development (BERD, therefore) on survival at the firm-level. To do so, we combine French datasets and estimated covariates.

Our paper revolves around two main databases. First, the R&D survey over the period 2006-2014, which provides firm-level data on R&D expenditures. We can use these information to know which firm innovates, the amount and, using the panel dimension, the frequency. As Bellégo and Dortet-Bernadet (2014) point out, this survey does not regroup all the firms' R&D activities. A sample of firms is selected each year, depending on their activity. Three possibilities arise. First, companies doing BERD for more than €750,000 are extensively surveyed. Second, companies that do less than €750,000 of BERD are interrogated for a maximum of two consecutive years. Third, firms suspected of investing in BERD, thanks to cross-referencing of firm-level information, are all surveyed. While the first two categories regroup existing firms that had at least once declared doing R&D activities in the past year, the third category is a set of companies that were never surveyed, but are likely to invest in innovative activities. However, and as Bellégo and Dortet-Bernadet (2014) show, firms that are less than two-year-old and the smallest firms have very few chances of being surveyed two consecutive years. One of the reasons is that smaller firms are less likely to have enough assets to meet the threshold of €750,000, and thus to be surveyed continuously. Moreover, even if this truncation did not exist, some firms would invest in such activities because of their unobserved characteristics. For these reasons, we can see that the selection process is not random. We then use a strategy that takes this into account to infer the amount of BERD invested by the firm is.

The second dataset is the official bulletin of civil and commercial announcements database (BODACC thereafter), which gives us information about firms' default between 2008 and 2016. In France, BODACC provides information only on legal procedure a firm is involved into. After reaching 45 consecutive days of insolvency, the French bankruptcy regime requires the triggering of a collective procedure — knowing that the decision on the procedure is left up to the Court.[3] There are three different procedures for companies in distress, ranked from the less to the most intrusive: the safeguard procedure, the reorganization procedure and the liquidation procedure. While the last two procedures are quite common,

[3] See Appendix A.

the safeguard one is both new and unusual.[4] It allows firms that are facing a critical situation, but not in a cessation of payment, to ask for the Court help, in order to maintain both activity and employment, while regulating liabilities. At the end of the safeguard plan, if it was not successful enough, the procedure can be converted to a reorganization or liquidation procedure depending on the situation of the debtor. In the reorganization procedure case, the judicial administrator can have an active or a passive role: the decision power will be reduced at the expense of the administrator in case of an active mission. The procedure can last at ten years at most for all companies, with the exception of farming companies (fifteen years).[5]

The liquidation procedure, similarly to the reorganization procedure, can be triggered only if the firm is in a state of insolvency. It can be opened either after the failure of the reorganization plan, or directly after the safeguard procedure if the company became unable to reimburse its creditors or directly opened after the insolvency if the firm is considered impossible to save. It lasts for two years maximum and is completed only if liabilities are fully reimbursed or if the assets are extinguished. Since safeguard procedure can be started without insolvency, the Court has to state whether or not the company needs its help. This rule is not as clear as the insolvency rule. For this reason, we will focus on the liquidation and reorganization procedures. The default date is defined as the date when procedure is triggered. This is an accountancy-based exit decision, and the decision does not even lie in the manager's hand. It is completely external to the firm, and, contrary to the economic-based decision, the literature does not consider this particular approach.

In addition, for firm-level variables such as assets, materials, revenue, the number of employee and value-added, we use the Unified Corporate Statistics System, the File approaching the results of the Elaboration of Annual Statistics of Companies, the Annual Declaration of Social Data and the Financial Links between Enterprises Survey (FICUS, FARE, DADS, and LiFi, respectively). Those databases are used to either compute or estimate our control variables. We restrict our sample to firms that have more than five employees and €5,000 of tangible assets so that we do not have to deal with the measurement problem due to small firms.

3.2 Selection equation

Since a limited number of firms are engaging R&D expenditures, a selection bias may exist. More precisely, our sample contains firms evenly and unevenly surveyed, i.e. large firms and smaller ones. In order to control the selection bias, we partially follow the CDM framework (Crépon et al., 1998). The equation model from the Tobit II (Amemiya, 1984) will allow us to assess all firms' R&D expenditures by controlling for the selection bias. The first step of the two-equation model is the selection equation which estimates the probability of engaging R&D activity for a given firm. The variable E_RD_{it}, our latent variable, is a binary variable capturing whether or not the firm i does R&D in year t. The equation is written as

[4] Safeguard procedure was introduced in 2005.

[5] A simplified safeguard procedure exists for large firms. To be eligible, the firm has to have at least 20 employees, a turnover greater than €3,000,000 before taxes, or a balance sheet greater than €1,500,000. The plan must be voted by creditors who detained at least two-thirds of the total debt. Note that a regular simplified procedure is different from a financial simplified safeguard procedure (which concerns firms deeply indebted to banks, with the majority of their financial creditors' supports).

follows:

$$E\_RD_{it} = \begin{cases} 1 & \text{if } E\_RD^*_{it} = \beta_1^{'} z_{1it} + \alpha_{1i} + \epsilon_{1it} > 0 \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

where $E\_RD^*_{it}$ is the latent variable and z_{1it} is the vector of independent variables predicting the R&D activity. We disaggregate the error term with α_{1i} the unobserved individual heterogeneity term, and ϵ_{1it} the idiosyncratic term. The second step is the interest equation which estimates the amount devoted in innovative activities by the firm. The *BERD* is positive if we observe it and zero otherwise. We estimate the following equation with the *BERD* in logarithm:

$$\log(\mathit{BERD}_{it}) = \begin{cases} \log(\mathit{BERD}^*_{it}) = \beta_2^{'} z_{2it} + \alpha_{2i} + \epsilon_{2it} & \text{if } E\_R\&D^*_{it} = 1 \\ -\infty & \text{otherwise} \end{cases} \tag{2}$$

where $\log(\mathit{BERD}^*_{it})$ is the latent variable for R&D expenditures and z_{2it} the vector of independent variables that predict the amount the firm i will invest in R&D activities. Again, in this equation, we split the error term in two, with α_{2i} the unobserved individual heterogeneity term and ϵ_{2it} the error term. Although we can estimate the two equations separately, they are not independent. We assume that error terms follow a bivariate distribution, conditional on the respective independent variables.[6] This distribution has a zero-mean, variances σ_1^2, which is set at 1 for identification purpose, and σ_2^2 and a covariance of $\sigma_{12} = \rho_{\epsilon_{1it},\epsilon_{2it}}\sigma_2$, with $\rho_{\epsilon_{1it},\epsilon_{2it}}$ being the correlation between error terms.

We then predict the amount of BERD each firm would have done, based on the TOBIT II model, and then use this generated regressor in our main model.

The specification of both equations (1) and (2) are very important because we need to predict accurately the amount of R&D expenditures for each firm. In order to be able to predict as accurately as possible, the choice of vectors of variables z_{1it} and z_{2it} is critical. Firstly, the vector z_{1it} contains the Herfindahl index, as a measure of local competition. As Aghion et al. (2005) and Gilbert (2006) pointed out, the effect of competition on innovation expenditures can be non-linear, with an inverted U-shape relationship. When the competition is low, the incentive to innovate is low too, but when a firm is too dominant or is part of a cartel, the incentive can also be low. It is computed at the two-digit NACE level as follows:

$$\text{Herfindahl}_{jt} \sum_{i=1}^{N_t^j} \left(\frac{Y_{it}}{\sum_{i=1}^{N_t^j} Y_{it}} \right)^2 \times 1000 \tag{3}$$

where Y_{it} is the output of firm *i* at time *t* in the sector *j*. It ranges between 0 and 1,000, the latter being the less competitive sector possible and 0 being the market's value with the highest competition. We use the deflated value-added as the output.

We also introduce the technology intensity level of the sector the firm belongs to, using the classification of Eurostat. At the end, we have 5 categories: high-technology manufacturing sectors, med-high-technology manufacturing sectors, med-low and low-technology manufacturing sectors, high-knowledge services sectors, low-knowledge services sectors.[7]

Secondly, as Klette and Kortum (2004) point out in its stylized facts, firm size is an important factor in the R&D activity

[6] It is important to highlight that the normality of the distribution is not crucial (Olsen, 1980).

[7] For more detailed information, see `https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf`.

decision. To take this effect into account, we introduce the number of employees in log by firm and year. Lastly, following Blanchard et al. (2005), Aw et al. (2007) and Vancauteren et al. (2015), we include dummies controlling for the group characteristics (being a part of a group and foreign control) and three trade status dummies (exporter, importer two-way trade). The foreign market exposition can have mixed effects on R&D investments. Imports for instance, can either reduce firms' R&D over sales ratio or imports of better quality inputs can maximize their chance of having a positive outcome for their innovative activities, (see Liu and Qiu, 2016). We also include both year and industry dummies to control for business cycle and industry characteristics. We also include a financial variable, the interest expenses over debt ratio.

In equation (2), the vector z_{2it} includes almost firm-specific and sector-specific controls as z_{1it} does. Some differences between z_{1it} and z_{2it} are required to be able to identify equation (2). For this reason, we use the turnover export's share instead of the trade status dummies, the foreign group membership and we have a financial variable, the debt over sales ratio, which is defined as the debts of the firm divided be the sales turnover. As proposed by Zabel (1992), we introduce the Mundlak correction (Mundlak, 1978), which allows for the correlation between regressors and unobserved heterogeneity in both equations.

3.3 Survival analysis

We implement a survival analysis to assess the impact of R&D expenditures on firms' survival. We use the model to predict the failure (default). Survival analysis revolves around four concepts: the density function, the cumulative distribution, the survival function, and the hazard rate. While the two latter are specific in the survival analysis literature, all of them are closely related. Let be T the duration, $T > 0$. The cumulative distribution is the probability that T is lower than a particular value x, i.e.:

$$F_T(x) = Pr[T < x], x \in \mathbb{R}_+^* \tag{4}$$

This is the fraction of firms that had been defaulting in x. Considering the density function of the duration, this is only is the derivative of the cumulative, given by:

$$f_T(x) = \frac{\partial F_T(x)}{\partial x} \tag{5}$$

If those two concepts are widely known, the duration data analysis's particularities are the survival function and the hazard rate. The survival function directly refers to the opposite of the cumulative distribution. While the cumulative distribution grows with the firms' "death", the survival function declines with them. This function is defined by the fraction of firms that did not exit at the time x, i.e.:

$$S_T(x) = Pr[T > x] = 1 - F_T(x) \tag{6}$$

Finally, the hazard rate is the conditional probability of defaulting in x, knowing that the firm was not defaulting before this date, i.e.:

$$\lambda_T(x) = \lim_{\Delta x \to 0} \frac{1}{\Delta x} Pr\left[x < T \leq \Delta x \mid T > x\right] = \frac{f_T(x)}{S_T(x)} \geq 0 \tag{7}$$

However, the survival analysis relies not only on descriptive statistics but also on more advanced models to explain the duration. The most commonly used models are the proportional hazard models (PH, therefor), such as Cox-PH model (Cox, 1972), or accelerated duration models. Those models can use parametric or semi-parametric specifications, according to the need for flexibility, to assess covariates' impact on duration. Even if basic models cannot consider a change in the covariate over time, more sophisticated models using spell and frailty specifications can take into account unobserved heterogeneity in addition to changes over time.

Because in our model we will use time-variant variables, with possible unobserved heterogeneity, we consider the use of shared frailty duration models. As Hougaard (1995) shows, this model is similar to Cox-PH model, with the addition of an unobserved heterogeneity term, that we note α_i. For the t^{th} year of observation of the i^{th} individual, we note T_{it} the survival time and C_{it} its censorship. We observe $Y_{it} = \min(T_{it}, C_{it})$ and the event indicator is $\delta_{it} = I_{\{T_{it} \leq C_{it}\}}$. Shared frailty model specifies the frailty variable's conditional risk function as follow:

$$\lambda_{it}\left(x \mid \alpha_i\right) = \alpha_i \lambda_0(x) \exp(\beta' Z_{it}) \tag{8}$$

where $\lambda_0(x)$ is the based-hazard function; $Z_{it} = \left(Z_{1it}, \dots, Z_{pit}\right)'$ the vector of explicative variables with a year (denoted t) and a firm dimension (denoted i), β the vector of corresponding parameters, and α_i are the unobserved random variables (the frailty variables), shared by the same firm i. We consider that α_i terms follow a gamma distribution, thus are independent and identically distributed random variables with an unit-mean and an unknown θ variance, as discussed by Hougaard (1995).[8]

The vector Z_{it} contains, among other control variables, the R&D expenditures or total factor productivity (TFP thereafter). Since we cannot observe TFP, we have to compute it with the method developed by Levinsohn and Petrin (2003). The results are reported in Table B.1 highlighting an heterogeneity between manufacturing sectors on how production factors impact the value added. The electricity, electronics and informatics products sector is the most capital-intensive industry, while the clothing industry is the most labor-intensive sector and the second most capital intensive. On the other hand, the food products, beverages and tobacco industry is less capital and labor intensive. Moreover, all these industries comprise roughly two-thirds of labor and one-third of capital, which is consistent with the literature.

However, TFP contains multiple factors that affect the firms value-added in addition to labor and capital. As Crépon et al. (1998) show, among other factors, firms' productivity and innovation activities are tightly entangled. This is the reason why it is impossible to use the TFP estimated in the main model. We use the log of BERD and its square, to estimate a fixed-effect model to extract the impact of innovation from the productivity index. We then compute the difference between the TFP the predicted value by the fixed-effect model (results are displayed in Table C.1), by subtract its linear prediction to the actual value estimated. By doing so, we obtain $\log(\widehat{\text{tfp}}_{it})$, i.e. the TFP (in logarithm) net of BERD.

Multiple other factors can impact the default, that is why we use additional control variables. First, we use the firm-specific variables: the group membership (as the head or only a subsidiary), and the foreign group membership. Second,

[8]Other distributions are possible, such as log-normal and positive stable distributions, but rapidly converge to a gamma distribution.

we also introduce the industry-related variable Herfindalh's concentration index (as explained in Section 3.2).

Because we are using accelerated duration models, we will not expose our results in term of impact of covariates on the probability of failing, but rather on the firms' survival, which is more in line with both the literature and the accelerated time failure model.

4 Results

4.1 Statistics

Since the results are mixed in the literature, we cannot have a preconceived idea about BERD's impact on firms' survival. However, some statistics displayed in Figure D.1 and Tables 1 and D.1 give us some insight into the behavior of firms in terms of BERD. First, the more the sector has a high technology–knowledge competition, the more firms invest. Thus large firms in high-technology manufacturing sectors and knowledge-intensive sectors have more BERD investments than their respective counterpart (see Table D.1). However, for firms in service industries, large firms operating in knowledge-intensive sectors invest three times more than the ones in less knowledge-intensive sectors. Even if large companies' gap is thin for the manufacturing firms, the one between intermediate-size companies denotes an important difference between them.

Second, despite those differences, we can see as an important gap between size class of firms in all those sectors. The vast majority of amount invested in innovative activities is the result of large companies' investment. More interestingly, the lower the technology/knowledge is required in the sector, the higher the gap is. The more the sector is technology- or knowledge-intensive, the smaller firms should invest to remain competitive and to maintain their market position. We should keep in mind that only the bigger firms are surveyed consistently over time, which could lead to an observation bias for the micro-companies and small and medium firms. Nonetheless, the difference is significant between intermediate-sized and large firms.

Table 1 displays descriptive statistics on the variables we use in our models, the Tobit and the survival. We see that firms in knowledge-intensive or high-technology sectors have a higher probability of investing in innovative activities, have a higher amount invested in BERD, both predicted by the Tobit, and observed. We also see that those firms are more often part of a multinational group or local group than other firms. Moreover, the firms are slightly bigger in terms of employment or liabilities, even if the employment gap is not important between High and Medium-High Technology sectors. Note that the average productivity index for non-defaulting firms, does not differ across manufacturing sectors. While the defaulting firms have a lower average-productivity index than their non-defaulting counterparts in the same sector, the difference between manufacturing sectors for failing companies is more revealing. The more the sector is technology-intensive, the lesser firms' productivity at the time of default is. This can be caused by the greater impact of innovation on the probability of exiting in the higher innovative sectors compared to the others. Another valid explanation would be the impact of innovations' investment with negative outcomes on these firms' efficiency. Unsuccessful outcome

	All			Never defaulting			Defaulting		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Foreign group membership$_{t-1}$	1,425,257	0.13	0.34	1,372,794	0.13	0.34	52,463	0.10	0.30
Share of export$_{t-1}$	1,425,257	0.05	0.15	1,372,794	0.05	0.16	52,463	0.05	0.14
Debt over sales ratio$_{t-1}$	1,425,257	0.40	0.94	1,372,794	0.40	0.96	52,463	0.48	0.37
Number of employees$_{t-1}$	1,425,257	2.92	0.99	1,372,794	2.92	1.00	52,463	2.93	0.86
Herfindahl index$_{t-1}$	1,425,257	13.82	38.18	1,372,794	13.75	38.10	52,463	15.78	40.18
Exporter only$_{t-1}$	1,425,257	0.05	0.22	1,372,794	0.05	0.22	52,463	0.06	0.24
Importer only$_{t-1}$	1,425,257	0.08	0.27	1,372,794	0.08	0.27	52,463	0.07	0.26
Both exporter and importer$_{t-1}$	1,425,257	0.15	0.36	1,372,794	0.15	0.36	52,463	0.14	0.35
Group membership$_{t-1}$	1,425,257	0.38	0.48	1,372,794	0.38	0.48	52,463	0.30	0.46
Number of employees$_{t-1}$	1,425,257	2.92	0.99	1,372,794	2.92	1.00	52,463	2.93	0.86
R&D activity (all sample)	1,425,257	0.03	0.16	1,372,794	0.03	0.16	52,463	0.02	0.14
Export activity	1,425,257	0.21	0.40	1,372,794	0.21	0.40	52,463	0.19	0.40
Number of employees	1,425,257	2.92	1.00	1,372,794	2.92	1.00	52,463	2.89	0.86
Foreign group membership	1,425,257	0.11	0.31	1,372,794	0.11	0.31	52,463	0.07	0.25
Herfindahl index	1,425,257	14.07	38.13	1,372,794	14.00	38.07	52,463	15.88	39.56

Table 1: Descriptive statistics of defaulting vs non defaulting firms: All sectors

may result in a loss of competitiveness, and it may be worsen in cutting edge sector, where innovation is crucial (Sueyoshi and Goto, 2009). This would be in line with the predictions of the active learning model developed by Ericson and Pakes (1995).

4.2 Selection equation

In Table 2 we display the estimation of equation (1) in column (1)and equation (2) i n columns (2) and (3). Note that the column (3) takes into account the selection bias. Therefore, this specification is more relevant. Moreover, we note a large and significant correlation between the idiosyncratic terms a.k.a "Heckman's ρ" (i.e. $\rho_{\epsilon_{1it},\epsilon_{2it}}$ in Table 2), comforting us in our choice of correcting sample selection bias.

The decision of doing R&D activities depends positively on the size of the firm the categories (being part of a group) and the participation in international trade (being exporter and/or importer variables have a positive coefficient). Considering the technology intensity of the firm's sector, the results differ across industry. Compare to the medium-low and low-tech manufacturing sector, all the coefficients are positive, except for the less knowledge-intensive services, indicating that the firms operating in this technology or knowledge intensive sectors, are more likely to engage innovative activities to better compete. This result is reaffirmed by the coefficient associated with the Herfindahl index. The more competition there is, the more firms are likely to do R&D investment.

In column (2) and (3), the dependent variable is BERD, which is continuous. The set of regressors slightly differs from the column (1), because of identification purpose.[9] As for the decision of R&D, we have some firm-specific and sector-specific determinants, which play a role in the amount invested. Regarding the exposure to the foreign markets, when a firm increases the share of exports in the overall turnover of one percentage point, it increases the assets invested in R&D by 0.1 percentage point, ceteris paribus. Exporting firms face a fierce competition, which force them to innovate (product

[9]Wherever possible, dummy variables have been replaced by continuous ones, which refers to common characteristics.

	(1) Equation of decision w/ selection effect	(2) Equation of interest w/out selection effect	(3) Equation of interest w/ selection effect
Herfindahl$_{t-1}$	−0.000***		
	(−2.801)		
Trade status:			
– *Exporter$_{t-1}$*	0.006***		
	(19.830)		
– *Importer$_{t-1}$*	0.001**		
	(1.993)		
– *Both$_{t-1}$*	0.001**		
	(2.360)		
Group membership:			
– *All$_{t-1}$*	0.000*		
	(1.908)		
– *Foreign$_{t-1}$*		−0.035**	−0.000**
		(−2.532)	(−2.438)
Share export$_{t-1}$		0.074**	0.001**
		(2.117)	(2.079)
Debt over sales ratio$_{t-1}$		−0.017	−0.000
		(0.894)	(−0.893)
Log number of Employees$_{t-1}$	0.005***	0.356***	0.035***
	(10.601)	(9.746)	(11.547)
Sector (ref: Medium-Low and Low Tech Manufacturing)			
– *High Technology Manufacturing*	0.022***	0.642***	0.150***
	(5.412)	(11.865)	(5.703)
– *Medium-High Technology Manufacturing*	0.012***	0.269***	0.076***
	(8.038)	(6.428)	(8.466)
– *Knowledge-Intensive Services*	0.015***	0.952***	0.110***
	(10.587)	(23.246)	(11.866)
– *Less Knowledge-Intensive Services*	−0.005***	0.314***	−0.033***
	(−8.571)	(6.092)	(−9.093)
# obs	1,425,257	36,210	1,425,257
# firms	173,672	9,139	173,672
Individual fixed effects correlation ($\rho_{\alpha_{1i},\alpha_{2i}}$)	0.117*	0.117*	0.117*
	(1.959)	(1.959)	(1.959)
Idiosyncratic terms correlation ($\rho_{\epsilon_{1it},\epsilon_{2it}}$)	−0.699***	−0.699***	−0.699***
	(−6.050)	(−6.050)	(−6.050)

Student-t computed with standard errors clustered at firm-level-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Tobit estimation – The determinants of R&D's activity

and/or quality) more than others. This result must be related to findings on trade status in column (1). Turning to the size of the firm, an increase of the number of employees by one percent is associated with an increase of the R&D investment by 3.8 percentage points. Once we have controlled for the other covariates, the financial health of the firm, through the debt over sales ratio, impacts to a lesser extent the amount invested compared to the other determinants. Besides, firms that belong to an international group, invest less in R&D than the others, because R&D activities are generally concentrated in the headquarter or in specific affiliates (vertical specialization). R&D investments are higher in high technology or knowledge intensive sectors. This is in line with our previous findings. Firms in high technology or knowledge intensive sectors invest in R&D more often and more substantially.

4.3 Survival analysis

The results of the survival model are displayed in Table 3. Columns (1) to (4) allows us to confront models, i.e., with and without the control variables and with and without the quadratic terms, to choose the most fitted specification. Firstly, the sign of the coefficient related to the BERD elasticity is sensitive to the inclusion of control variables, regardless of the presence of the quadratic terms. Second, the introduction of quadratic terms allows us to understand better the impact of firms' productivity and BERD on survival. For these reasons, our preferred specification is displayed in column (4).

Interestingly, we find that productivity and survival have a positive relationship and have an exponential relationship. This finding means that the more a firm is efficient, the more likely it will survive a longer period. More than that, since the quadratic term is both positive and significant, the effect will be greater for the highest-performing firms. On the other hand, we find that the BERD investment has a U-shaped relationship with the survival probability. At first, the more a firm invests in BERD, the less likely it will survive. Then, after reaching a certain level of investment, BERD increases the probability of staying in the market, which is consistent with the risk inherent in such investments. This effect is not surprising since low investments in such risky activities are a financial burden with a low probability of high enough returns. This financial constraint can add to others, put the firm in a more difficult situation, and precipitate the firm's default. On the other hand, high enough investment in innovative activities should result in more frequent positive outcomes, thus increasing the firm's survival. In line with the prediction of the active learning model developed by Ericson and Pakes (1995), the fiercer the competition is, the higher the investments firms consent in such activities are. Overall, concerning the control variables, we see that, contrary to what we expected, being an exporter does not prevent from exiting the market. However, it is not a surprise either since exporting is risky as well. On the contrary, being a large firm or belonging to a foreign group prevents entry into a bankruptcy procedure. Firms that operate in sectors with higher concentrations exhibit a lower probability of surviving. Although Herfindahl's index, Conc_{it} seems to have a U-shape relationship, the quadratic term coefficient is very small, which leads us to believe that the positive effect is negligible compared to the negative effect.

In columns (5) to (9), we examine the sectoral heterogeneity. On one hand, in column (5) and (6) we examine the impact of each variable for the survival of the firms in each technology level, respectively high and low. On the other hand, in column (7) to (9) we further decompose the technology level across manufacturing (column (7) and (8)) and services sectors (column (9)). The effects of TFP and BERD on firm survival remain stable whatever the technological intensity of the sectors. However, as predicted with the hypothesis H3-b), for manufacturing sectors, the magnitude of the TFP is greater in high-tech sectors than in low-tech intensive ones. The results of the regression for the overall technological levels do not verify this hypothesis. One explanation might arise from the differences of firms in both manufacturing and service sectors. In fact, results displayed in the columns (7) and (9) point towards different behaviors in those sectors.

According to columns (7)-(9), we note that for manufacturing firms, the effect of being an exporter is either insignificant

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Technology level		Manufacturing		Services[a]
					High	Low	High-&Med-Tech	Low-Tech	High-Know
$\log(\widehat{\text{tfp}}_{it})$	2.645***	2.293***	4.051***	3.869***	2.596***	4.178***	4.708***	3.988***	2.149***
	(0.053)	(0.054)	(0.050)	(0.050)	(0.112)	(0.057)	(0.281)	(0.109)	(0.125)
$\log(\widehat{\text{tfp}}_{it})^2$			0.392***	0.372***	0.228***	0.417***	0.435***	0.366***	0.195***
			(0.010)	(0.009)	(0.016)	(0.013)	(0.049)	(0.018)	(0.020)
$\log(\widehat{\text{BERD}}_{it})$	0.518***	−0.607***	0.649***	−1.522***	−0.777**	−4.164***	−2.523***	−3.936***	−1.100*
	(0.088)	(0.083)	(0.181)	(0.221)	(0.305)	(0.536)	(0.465)	(0.622)	(0.583)
$\log(\widehat{\text{BERD}}_{it})^2$			−0.060	0.229***	0.116**	0.948***	0.262***	0.971***	0.216*
			(0.038)	(0.052)	(0.058)	(0.221)	(0.078)	(0.247)	(0.128)
Exporter_{it}		−0.119**		−0.105*	−0.441***	−0.095	−0.428	0.488***	−0.723***
		(0.059)		(0.062)	(0.167)	(0.068)	(0.269)	(0.109)	(0.260)
$\log(\text{size}_{it})$		0.805***		0.614***	0.659***	0.639***	1.528***	0.422***	0.537***
		(0.030)		(0.031)	(0.087)	(0.034)	(0.216)	(0.071)	(0.095)
Foreign group membership$_{it}$		2.502***		2.537***	2.333***	2.613***	3.029***	2.668***	2.033***
		(0.087)		(0.098)	(0.225)	(0.110)	(0.384)	(0.198)	(0.274)
Conc_{it}		−0.007***		−0.012***	−0.034***	−0.009***	−0.001	0.012***	−0.034***
		(0.001)		(0.001)	(0.003)	(0.001)	(0.023)	(0.004)	(0.004)
Conc^2_{it}				0.000***	0.000***	0.000***	−0.000	−0.000*	0.000***
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	19.390***	16.480***	21.960***	19.480***	21.340***	19.020***	18.700***	20.610***	21.670***
	(0.101)	(0.130)	(0.127)	(0.160)	(0.467)	(0.171)	(0.934)	(0.339)	(0.569)
# obs	1,417,815	1,417,815	1,417,815	1,417,815	233,799	1,184,016	53,392	256,452	180,407
# of firms	173,672	173,672	173,672	173,672	31,968	144,171	7,093	32,954	24,953
Log-likelihood	−102,672	−101,599	−99,927	−99,158	−13,661	−85,278	−3,439	−21,044	−10,137
Likelihood-ratio test	564.000	721.000	98.820	259.200	11.200	302.600	2.477	2.470	11.920
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.058	0.058	0.000
$\sigma^{(b)}$	5.179	4.950	6.040	5.736	6.403	5.568	5.992	6.054	6.419
$\theta^{(c)}$	8.026	9.004	1.538	2.788	2.149	3.113	0.943	0.419	3.276

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Probability of not being involved in a legal procedure - Full survival model

[a] Because of a convergence issue, the results for Low-Knowledge Services sectors are not displayed.
[b] Ancillary parameters of the log-normal distribution.
[c] Variance of α_i.

or positive on survival, while it is significantly negative for high-knowledge intensive services, indicating that export activity is associated with higher risks and costs in case of services than in case of manufacturing. Considering the firm's size, the magnitude of the effect is greater in high-technology intensive manufacturing sectors than in the other two. In addition, being part of a foreign group have a more significant impact on high-technology intensive manufacturing sectors than the others. Finally, even if the Herfindahl concentration index on survival is insignificant only for high-technology intensive manufacturing sectors, the effect differs for low-technology intensive manufacturing sectors (inverted U-shape relationship) compared to high knowledge-intensive services sectors (U-shaped relationship).

Concerning the interest variables, in column (7), the firms in the high- and med-high-technology intensive manufacturing sectors display a more important role of TFP in survival than in the high-knowledge intensive services sectors, displayed in column (9). However, the magnitude is similar in the low-technology-intensive manufacturing sector. That seems to point to an ”efficiency premia” in the manufacturing sector, at least compared to high-knowledge intensive service sectors. Considering the BERD's effect on survival, the magnitudes are different across sectors. However, only the turning points will discriminate where BERD's marginal effect will be positive. Indeed, since the effects have opposite signs, the marginal effect of R&D investments on survival is, at first, negative and then positive; thus, we have to identify the turning point. This well-known turning point is such as the marginal effect is equal to zero. Considering the amount invested in BERD, the turning point is the point from where each euro invested will have a positive impact on the survival probability.[10] We computed the thresholds for the different sectors, and results are display in Table 4 and shown graphically in Figure 1. We first see that the turning points depend dramatically on sectors. The more a sector required innovating to be competitive, the larger is the threshold. For manufacturing firms, low-technology intensive sectors have the lowest amount required (€7,589.580), while the high- and med-high-technology intensive sectors have the highest one (€123,332.690). However, the level of investment firms have to make also depends on the sector. The higher the threshold is, the more firms have to invest to reach the required threshold. In the manufacturing high-technology sectors and low-technology sectors, the average amounts invested for firms that invest over the threshold are respectively €566,497.690 and €26,542.100. However, the vast majority of these firms are below the thresholds, suggesting that only a few firms are able to increase their survival probability only thanks to their investment in innovative activities. Other firms have to rely on other factors, such as their productivity.

Although these non-linear effects of R&D expenditures have the same shape across different sectors, as Figure 1 This finding may confirm that investing in R&D, even if it can improve the firm competitiveness in case of successful outcomes, is a risky and costly activity. In Figure 1c, i.e. for high-tech intensity sectors (both manufacturing and services), we can see that, after the turning point, the impact of amount invested in R&D on survival slows down. So, for larger investments, the average effect of the amount invested does not have an important impact on the firm's survival. Moreover, for those firms, this negative impact on their survival is balanced by the other factors, such as productivity and the size.

However, we can expect heterogeneity between firms, according to their efficiency. It is only natural to expect a

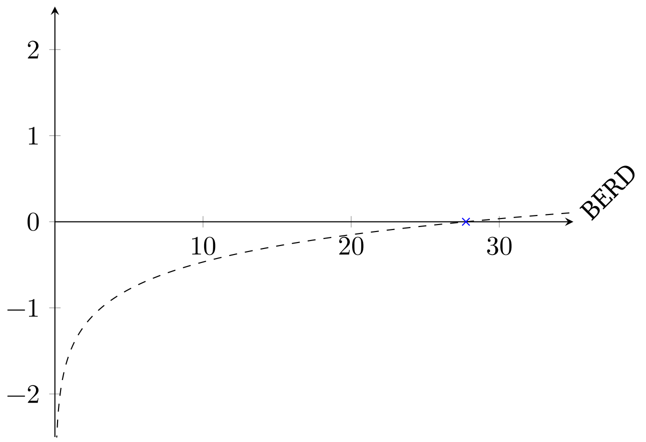
[10]To compute the Turning Point, we differenciate the function by $\log(\text{BERD}_{it})$, i.e.:
$$\frac{\partial\beta_1 \times \log(\text{BERD}_{it} + \beta_2 \times \log(\text{BERD}_{it})^2}{\partial \log(\text{BERD}_{it})} = 0 \Longleftrightarrow \text{BERD}_{it} = \exp\left(-\frac{\beta_1}{2\times\beta_2}\right).$$

		Threshold (in euros)		Number of firms	Share	Average
All		27,747.450	Below	1,419,046	99.56%	1,032.78
			Above	6,211	0.44%	175,750.08
Tech-level	High-tech	28,478.170	Below	229,358	97.67%	1,144.86
			Above	5,472	2.33%	192,734.58
	Low-tech	8,990.810	Below	1,188,923	99.87%	1,010.77
			Above	1,504	0.13%	34,245.80
Manufacturing	High-manuf	123,332.690	Below	51,843	96.43%	1,761.79
			Above	1,920	3.57%	566,497.69
	Low-manuf	7,589.580	Below	257,047	99.39%	1,043.68
			Above	1,584	0.61%	26,542.10
Services	High-serv	12,759.760	Below	178,695	98.69%	1,040.89
			Above	2,372	1.31%	108,894.77

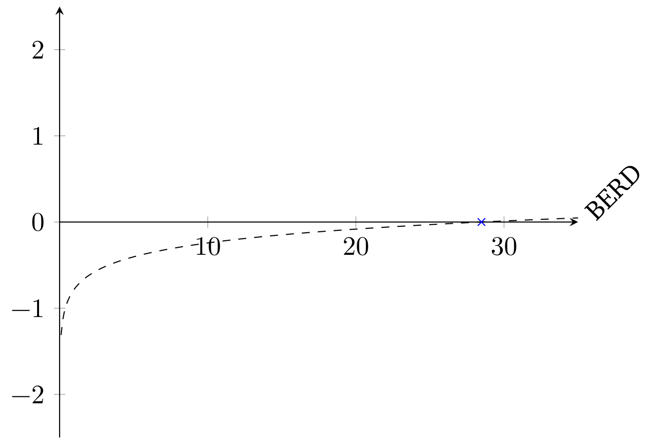
Table 4: Number of firms above or below the thresholds of BERD's marginal effects

productive firm to need a higher level of investment in R&D than a less productive one. That is why we needed to consider this interaction between TFP and BERD. The results are displayed in Table 5 and in Figure E.1. Then, we augment our model by including an interaction term of BERD with TFP as an explanatory variable. This interaction term should capture the productivity net of R&D investments as the TFP measurement may contain various factors such as R&D expenditures or management skills. Results from Table 5 suggest that the introduction of this interaction term does not affect our results. For the whole sample, the coefficient of the interaction is negative and significant. The result is similar for the other sectors, except for high-knowledge service sectors and the overall high technology sectors, for which the coefficient are insignificant. However, since the high-tech manufacturing sectors have a significant impact of the cross term, the insignificance of this term for the overall high technology sectors might come from the insignificance of the service sectors. This negative relationship can confirm that the more a firm is productive, the more it must invest in innovative activities to increase its survival likelihood. This result contradict the hypothesis H1). Thus, we can see this variable as a re-scale of the turning point, which considers the net firms' efficiency level. Only significant investments in R&D protect firms. The more a firm is already efficient, the more it must invest to have a positive effect on its survival. However, the more a firm is efficient, the more likely it will survive. These results confirm hypotheses H2) and H3-a), but also indicate a negative side of the investment. When the amount invested is low, the BERD represents a burden for the firm survival due to the low probability of successful outcome, while the effect of BERD on survival turns to be positive as the firm consents to invest more extensively.

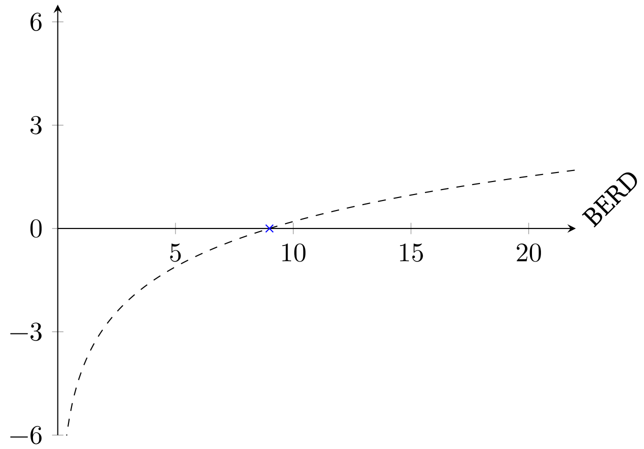
Considering the turning points of BERD with the inclusion of the interaction term displayed in Figure E.1, we see the heterogeneity across sectors. For high technology-intensity sectors, the importance of high investments for high productive firms is even more accentuated. For the high-technology level and high-knowledge intensive services sectors, respectively



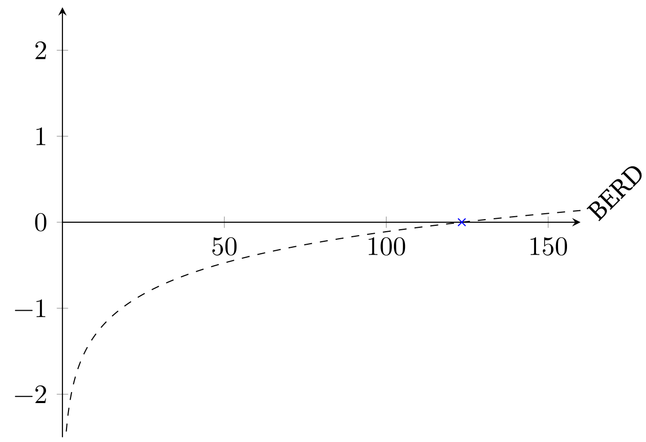
(a) All Sectors



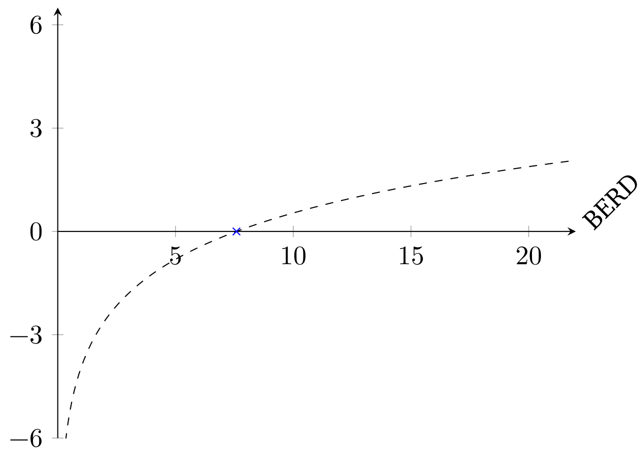
(b) High-Technology Sectors



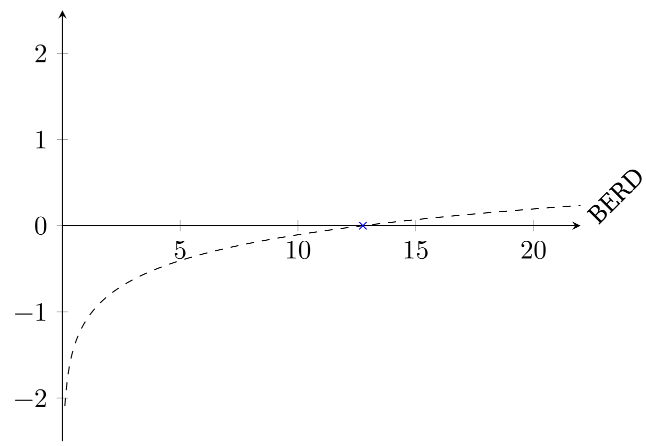
(c) Low-Technology Sectors



(d) High- & Med-High-Tech Manufacturing Sectors



(e) Low-Tech Manufacturing Sectors



(f) High-Knowledge Services Sectors

Figure 1: BERD's turning points (in thousand euros)

columns (2) and (6) of Table 5, Figure E.1b and Figure E.1f, effect of the interaction term on firm's survival is insignificant.[11] Nonetheless, this does not necessarily point toward an absence of effect, but might instead signify that an even higher level of investment should be required for the most efficient firms. Moreover the low magnitude of those terms leads to higher

[11]When computing the Turning Points, the differenciation leads to this new expression: $\mathrm{BERD}_{it} = \exp\left(-\frac{\beta_1 + \beta_3 \times \log(\mathrm{tfp}_{it})}{2 \times \beta_2}\right)$, which includes the productivity inside.

	(1)	(2)	(3)	(4)	(5)	(6)
		Technology level		Manufacturing		Services
	All	High	Low	High-&Med-Tech	Low-Tech	High-Know[(a)]
$\log(\widehat{\text{tfp}}_{it})$	3.924***	2.611***	4.251***	5.207***	4.203***	2.158***
	(0.051)	(0.116)	(0.058)	(0.324)	(0.114)	(0.127)
$\log(\widehat{\text{tfp}}_{it})^2$	0.378***	0.230***	0.429***	0.490***	0.392***	0.195***
	(0.009)	(0.016)	(0.014)	(0.061)	(0.020)	(0.020)
$\log(\widehat{\text{BERD}}_{it})$	−1.691***	−0.784***	−5.633***	−2.713***	−5.591***	−1.040*
	(0.215)	(0.304)	(0.565)	(0.461)	(0.673)	(0.591)
$\log(\widehat{\text{BERD}}_{it})^2$	0.339***	0.122**	2.528***	0.319***	2.409***	0.220*
	(0.055)	(0.059)	(0.348)	(0.080)	(0.376)	(0.126)
$\log(\widehat{\text{tfp}}_{it}) \times \log(\widehat{\text{BERD}}_{it})$	−0.931***	−0.074	−3.044***	−0.688***	−2.776***	−0.112
	(0.116)	(0.136)	(0.309)	(0.195)	(0.327)	(0.248)
Exporter_{it}	−0.110*	−0.441***	−0.090	−0.430	0.521***	−0.729***
	(0.062)	(0.167)	(0.068)	(0.269)	(0.110)	(0.260)
$\log(\text{size}_{it})$	0.610***	0.657***	0.636***	1.447***	0.416***	0.536***
	(0.031)	(0.087)	(0.034)	(0.213)	(0.071)	(0.095)
Foreign group membership$_{it}$	2.512***	2.328***	2.585***	2.947***	2.624***	2.032***
	(0.098)	(0.225)	(0.109)	(0.379)	(0.196)	(0.274)
Conc_{it}	−0.012***	−0.034***	−0.010***	−0.004	0.012***	−0.034***
	(0.001)	(0.003)	(0.001)	(0.023)	(0.004)	(0.004)
Conc^2_{it}	0.000***	0.000***	0.000***	−0.000	−0.000*	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	19.470***	21.330***	19.010***	19.110***	20.620***	21.670***
	(0.159)	(0.467)	(0.170)	(0.917)	(0.334)	(0.570)
# obs	1,417,815	233,799	1,184,016	53,392	256,452	180,407
# of firms	173,672	31,968	144,171	7,093	32,954	24,953
Log-likelihood	−99,128	−13,661	−85,229	−3,432	−21,009	−10,137
Likelihood-ratio test	270.700	11.340	314.600	3.109	3.929	11.830
p-value	0.000	0.000	0.000	0.039	0.024	0.000
σ[(b)]	5.726	6.401	5.556	5.968	6.020	6.421
θ[(c)]	2.831	2.162	3.154	0.977	0.508	3.261

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Probability of not being involved in a legal procedure - Full survival model with cross term

[(a)] Due to convergence issue, the results for Low-Knowledge Services sectors are not displayed.
[(b)] Ancillary parameters of the log-normal distribution.
[(c)] Variance of α_i.

level of investment needed, especially for highly productive firms.

5 Conclusion

The R&D is a risky investment and might put the firm in a difficult financial situation, and even lead to bankruptcy in the worse case. The literature has highlighted both the importance and the risk of innovation activities for firms dynamics. As the active learning framework points-out, firms have the incentive to invest in innovative activities to try to improve their performances. When the investment is not successful enough, compared to the other firms, it becomes a burden for this firm which might even accelerate its failure.

In this paper, we contribute to the existing literature. Firstly, we use BODACC database to discriminate "true" exit from the market. Secondly, we concentrate our study on the extensive margin of R&D, while most studies use the intensive margin. Thirdly, we use a methodology allowing us to tackle both the issue of right-censoring and unobserved heterogeneity with the shared-frailty duration analysis. Lastly, we use a selection equation to treat the auto-selection issue of R&D investment.

Based on large panel databases on French firms, we find that firm's investment in R&D has an U-shaped relationship with firm-survival. For small amount of BERD, the survival probability decreases while it turns positive for larger amounts. This suggest that firms should invest substantial amounts in R&D in order to mitigate the burden of this highly illiquid investments. According to our estimates, this result is even stronger for high-tech industries compare to lower-tech ones indicating that the level of technology required to perform in the sector matters.

We also see the importance of helping firms to invest in innovative activities. Our paper brings public policy recommendation that are twofold. First, encouraging firms to invest larger amount in such activities should help them to overcome the negative effect because there is a positive relationship between the level of R&D investment and the firm survival probability. Second, there is a high disparity of the effect of BERD across sectors and firms level of productivity. The lower their efficiency is, the higher the return of helping them to innovate could be. In all sectors, the positive effect of R&D investment happens at lower amount for lower level of efficiency, and could raise their survival. For this reason, it might be more cost-effective to help those firms, rather than highly efficient firms that require higher investments and already have higher survival probability thanks to their productivity.

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Appendices

A Legal procedures

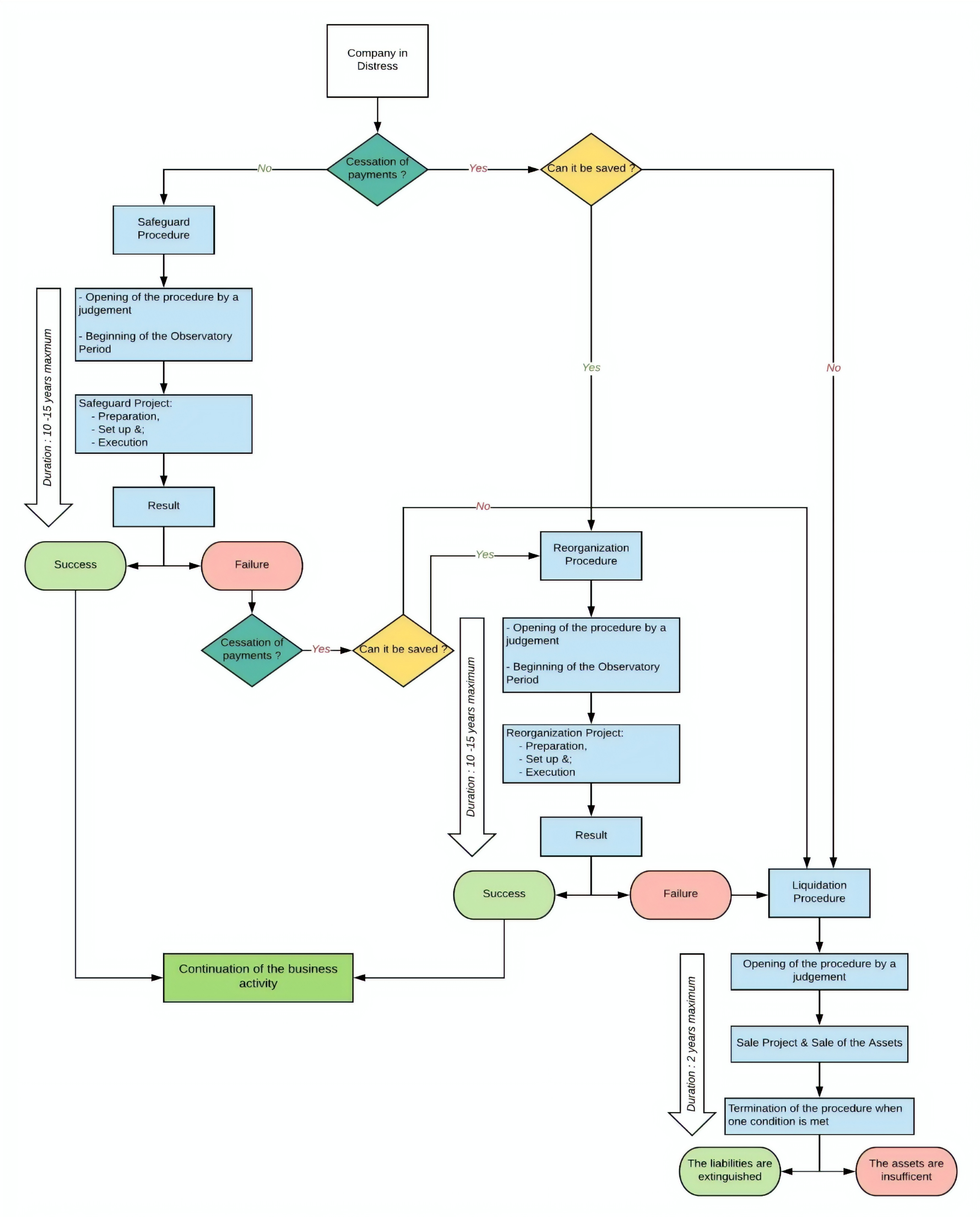


Figure A.1: French system of legal procedures

B Total factor productivity

Variables	(1) Food products, beverages and tobacco	(2) Other industrial products, coking and refining	(3) Electrics, electronics, informatics products	(4) Transporting materials	(5) Clothing industries	(6) Wood and paper industries	(7) Construction industries
l_t	0.537***	0.613***	0.554***	0.637***	0.652***	0.617***	0.616***
	(0.012)	(0.007)	(0.015)	(0.031)	(0.014)	(0.015)	(0.006)
$k_{t\text{-}1}$	0.185***	0.300***	0.357***	0.246***	0.341***	0.229***	0.258***
	(0.013)	(0.011)	(0.025)	(0.050)	(0.035)	(0.024)	(0.009)
Observations	65,419	153,000	34,424	8,797	16,286	34,737	254,964

Variables	(8) Wholesale and retail trade, transport, accommodation and catering	(9) Information and communication industries	(10) Financial activities and insurance industries	(11) Real estate activities	(12) Legal, accounting, management, architectural, engineering, control and technical analysis activities	(13) Other scientific and technical activities
l_t	0.599***	0.717***	0.507***	0.602***	0.608***	0.603***
	(0.004)	(0.015)	(0.040)	(0.022)	(0.009)	(0.006)
$k_{t\text{-}1}$	0.222***	0.181***	0.150***	0.290***	0.330***	0.236***
	(0.005)	(0.017)	(0.037)	(0.059)	(0.017)	(0.014)
Observations	608,474	40,692	9,632	23,193	102,628	72,712

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.1: Estimation of total factor productivity, 2006 – 2014

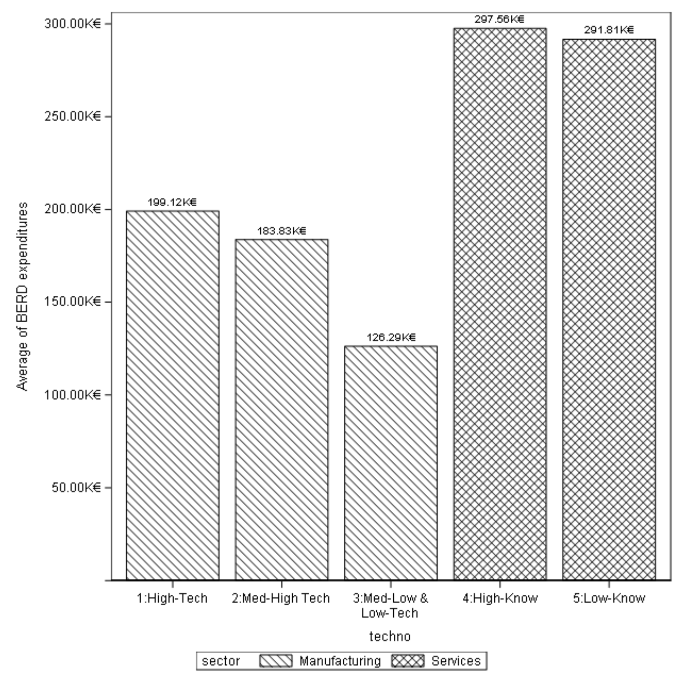
C Panel Fixed-effect estimation of TFP

	(1)	(2)
$\log\left(\widehat{\text{BERD}}_{it}\right)$	−0.047***	−0.077***
	(0.008)	(0.016)
$\log\left(\widehat{\text{BERD}}_{it}\right)^2$		0.006**
		(0.003)
Constant	3.693***	3.694***
	(0.000)	(0.001)
# of obs	1,425,257	1,425,257
R-squared	0.000	0.000
# of firms	173,672	173,672
Industry FE	No	No

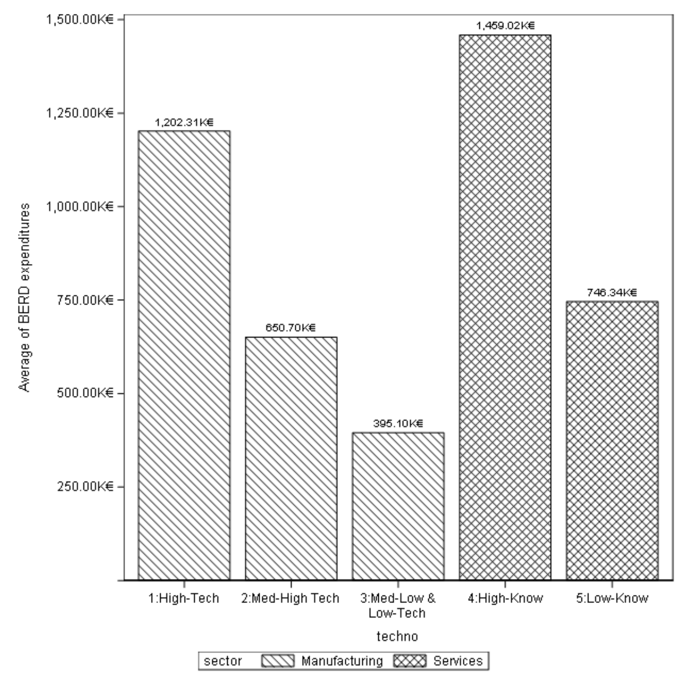
Standard errors clustered at firm-level in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table C.1: Fixed-effect estimation of TFP

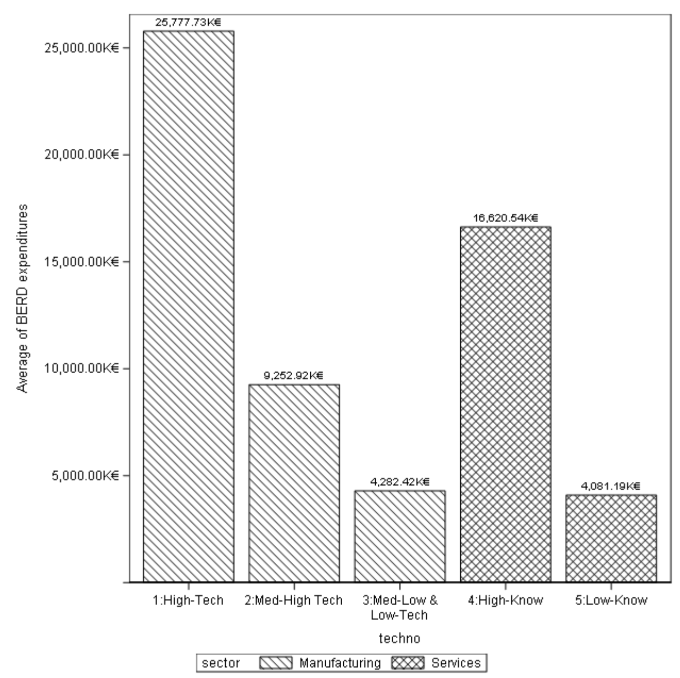
D Average amount invested in BERD



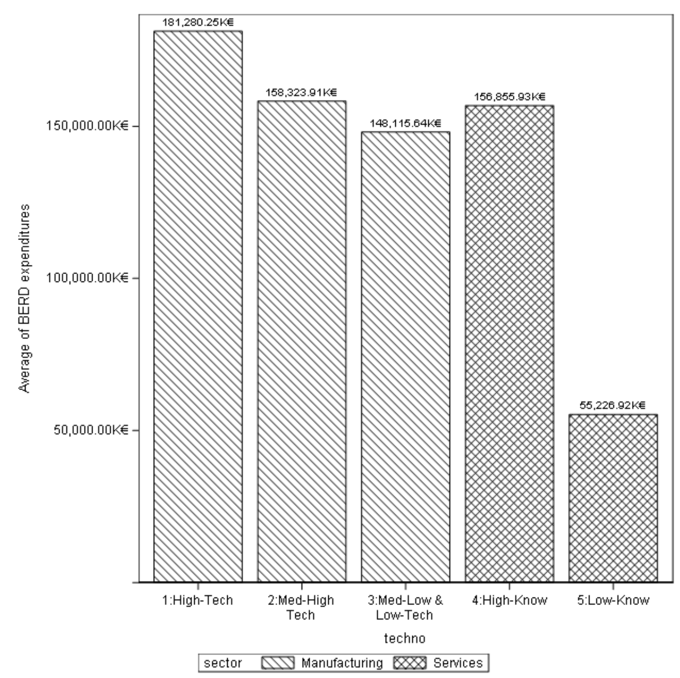
(a) Micro entreprises



(b) Small entreprises



(c) Intermediate entreprises



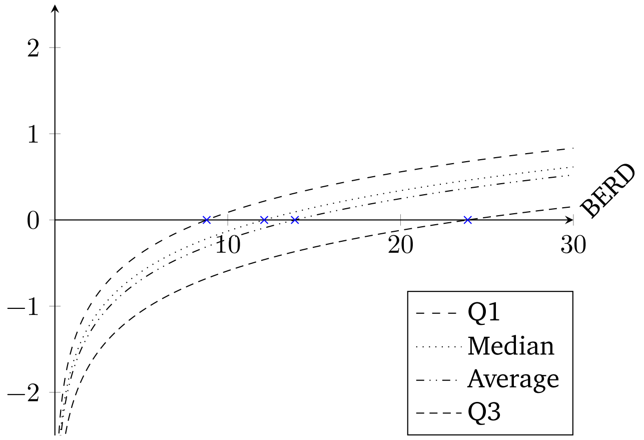
(d) Large entreprises

Figure D.1: Average amount invested in BERD according size across Eurostat technological sector classification–Services firms

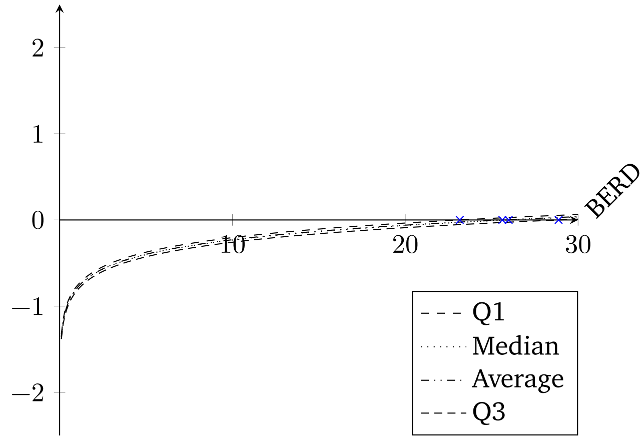
Sector	Technology	Size	Average BERD amount (in K€)	Overall share	In-tech-level share	In-firm size share
Manuf	High Tech	Micro	199.12	0.03%	0.10%	18.12%
		Small	1202.31	0.16%	0.58%	27.00%
		Intermediate	25777.73	3.37%	12.37%	42.95%
		Large	181280.25	23.69%	86.96%	25.90%
	Med-High Tech	Micro	183.83	0.02%	0.11%	16.73%
		Small	650.70	0.09%	0.39%	14.61%
		Intermediate	9252.92	1.21%	5.49%	15.42%
		Large	158323.91	20.69%	94.01%	22.62%
	Low Tech	Micro	126.29	0.02%	0.08%	11.50%
		Small	395.10	0.05%	0.26%	8.87%
		Intermediate	4282.42	0.56%	2.80%	7.14%
		Large	148115.64	19.35%	96.86%	21.17%
Services	High Knowledge	Micro	297.56	0.04%	0.17%	27.09%
		Small	1459.02	0.19%	0.83%	32.76%
		Intermediate	16620.54	2.17%	9.48%	27.69%
		Large	156855.93	20.49%	89.51%	22.41%
	Low Knowledge	Micro	291.81	0.04%	0.48%	26.56%
		Small	746.34	0.10%	1.24%	16.76%
		Intermediate	4081.19	0.53%	6.76%	6.80%
		Large	55226.92	7.22%	91.52%	7.89%

Table D.1: BERD statistics

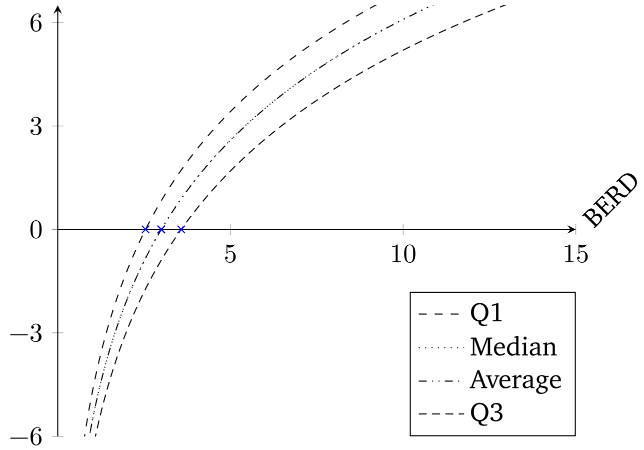
E Turning points with TFP cross-term



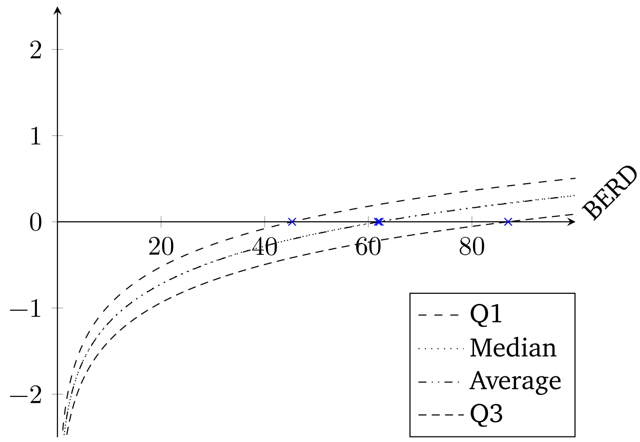
(a) All Sectors



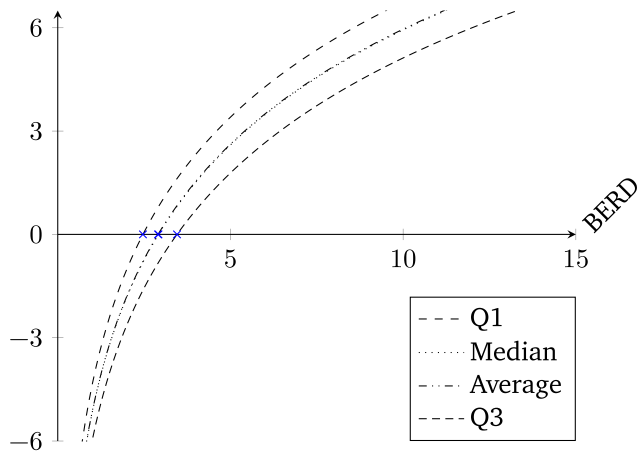
(b) High-Technology Sectors



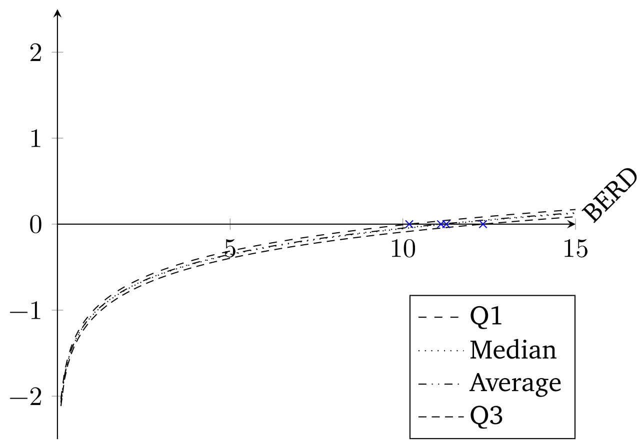
(c) Low-Technology Sectors



(d) High- & Med-High-Technology Manufacturing Sectors



(e) Low-Technology Manufacturing Sectors



(f) High-Knowledge Services Sectors

Figure E.1: BERD's turning points (in thousand euros)