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Determinants of firms' efficiency: do innovations and finance constraints matter? The case of European SMEs

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Abstract

This paper aims at investigating the relationship between firms' profit efficiency, access to finance and innovation activities. We enrich our understanding on firms' performance by adopting the stochastic frontier approach (SFA), which allows us to estimate profit functions and to obtain efficiency scores for a large sample of European firms. We pioneer the use of a novel dataset that merges survey-based data derived from the ECB Survey on access to finance for enterprises (SAFE) with balance sheet information. Our evidence documents that credit constrained firms display an incentive to improve their efficiency in order to increase profitability. Among firms that have embarked in product innovation, those in the industry and high-tech sectors see their effort translated in higher profit efficiency. From a policy perspective, our results could help to better understand the link between innovation, financial constraints and efficiency, which goes beyond the idea that easier access to finance is the *panacea* to get higher profit efficiency.

Keywords: Stochastic Frontier Approach, access to finance, innovation, survey data

JEL Classification code: D22 D24 L23 O31 C33

Non-technical summary

Innovation is a crucial aspect to foster firm performance and promote economic development. With the launch of new products and services in the market, firms attain a strategic advantage over competitors. However, obtaining finance for innovation is often difficult, given the uncertainty related to innovative projects and the presence of asymmetric information in financial markets. Financial constraints are particularly binding for small- and medium- sized enterprises (SMEs), which often suffer due to lack of transparencies on their credit records and ability to provide collateral.

The aim of this paper is to investigate the interplay between innovations efforts, obstacles to access to finance and profit efficiency. We use a novel firm-level data for a large sample of European SMEs and large enterprises over the period 2009-2017. The dataset combines survey-based data derived from the ECB "Survey on access to finance for enterprises" (SAFE) with balance sheet information – from Amadeus by Bureau van Dijk. Based on the survey data, we construct several indicators of firms' innovativeness and financing obstacles, while the financial statements allow us to retrieve data on output and input variables to define firms' costs and profits.

Technically, we enrich our understanding on firms' performance by adopting the stochastic frontier approach to estimate profits functions and to obtain efficiency scores for the firms in our sample. To take into account the different technologies and production functions across sectors, we estimate different frontiers for two main productive sectors: Industry and Services. Additionally, we complement our analysis with the Eurostat classification on high-technology industry and knowledge-intensive services. Interestingly, we show that high-technology/knowledge-intensive companies in the manufacturing and services turn to be more similar to each other than highly technology/knowledge-intensive and low technology/knowledge intensive within industries and services.

The main findings of the paper confirm that the impact of innovation on firm efficiency depends on sector characteristics. Specifically, for high-technology and knowledge-intensive companies, product innovation has a strong positive impact on profit efficiency while this seems not to be the case for firms in services.

Additionally, we provide evidence that, in the presence of market failure, financial constraints induce firms to improve efficiency to reduce their risk of failure and guarantee positive profits. This is independent from the macro sector disaggregation (Industry and Services), while Low-Tech firms are induced to be more efficient to enhance their profitability than High-Tech firms.

The policy implications of these results are not negligible. Our results give support to the line of firm-level policy interventions directly aimed at mitigating the underinvestment in R&D in Europe which take into account firm heterogeneity across technology and knowledge intensity sectors. Furthermore, our evidence could help to better understand the link between innovation, financial constraints and efficiency, which goes beyond the idea that easier access to finance is the *panacea* to get higher profit efficiency. What seems more important is the support provided to businesses to be competitive by encouraging them to adopt new business models and innovative practices.

1. Introduction and research hypotheses

This paper aims at investigating whether innovations efforts and obstacles in access to finance affect firms' profit efficiency, using firm-level data for a large sample of European SMEs over the period 2009-2017. Assessing the implications for firms' efficiency is relevant, especially after the global crisis where uncertainty about growth prospects had reinforced concerns in many European countries.

Despite the policy relevance of this topic, the fundamental assumptions underlying the link have remained largely unexplored. Indeed, the related literature has mainly focused on some aspects like financial constraints and productivity (Butler and Cornaggia, 2011; Ferrando and Ruggieri, 2018); productivity and innovation (Calza *et al.*, 2018; Dabla-Norris *et al.*, 2012), access to finance and innovation (Fombang and Adjasi, 2018).

Many of these studies argue that lower financial constraints exert a positive effect on innovation (Aghion *et al*., 2010, and Aghion *et al*., 2012, for France, and Manaresi and Pierri, 2017, for Italy) as firms exposed to higher financial constraints lower their investment, in particular on assets that have a strong impact on productivity. By contrast, the strand of the literature focusing on the cleansing "Schumpeterian" effect of financial constraints points to the fact that the highest productive firms crowd out the least efficient ones. In the environment of low real interest rates and financial constraints which characterised the period just before the financial crisis, the cleansing mechanism has been weakened with a detrimental impact on average productive growth (Gopinath *et al*., 2017; Cette *et al*., 2016; Gropp *et al*., 2017).

While few studies – closely related with our research target – have investigated the interplay between efficiency and financially constrained firms (Wang, 2003; Sena, 2006; Maietta and Sena, 2010; Bhaumik *et al*., 2012), the literature that has directly focused on the relation between innovation and efficiency is scant, and has mainly concentrated on the link between innovation and firm profitability (Zorzo *et al*., 2017).

As for the interplay between financial constraints and efficiency, it is indisputable that the increase in the cost of borrowing has a negative impact on investment. Due to the presence of information asymmetries, borrowing external funds for firms turns to be more expensive than using internal finance (Nickell and Nicolitsas, 1999). In this circumstance firms may have an incentive to improve efficiency in order to reduce the risk of failure (Sena, 2006; Maietta and Sena, 2010; Bhaumik *et al*., 2012).

With regards to the link between innovation and efficiency, the relationship is complex and contingent to several factors. Efficiency in production function focuses on the relationships between inputs and outputs (Farrell, 1957). A production plan is called efficient if it is not possible to produce more using the same inputs, or to reduce these inputs leaving the output unchanged. Inefficient firms can reduce expenses that are related to the revenues. These efficiency gains, though not necessarily, require reducing costs, but also increasing revenues that could derive from investments in innovation (intangibles). The innovation efforts of firms and the developments of new products or services are aimed at attaining a strategic advantage over competitors and leveraging revenues. As far as this link is concerned, some research provides support to the positive relationship between product innovation and firm profitability (Geroski *et al*., 1993; Leiponen, 2000; Cefis and Ciccarelli, 2005), which may arise because either innovative firms are able to protect their new products from the competition, or they display higher internal capabilities, compared to non-innovators (Love *et al*., 2009). Other studies point out that no clear relationship might be found between technological innovation and firm performance (Díaz-Díaz *et al*., 2008), when analysing the short term effects (Deeds, 2001; George *et al*., 2002; Le *et al*., 2006) and the long term indirect effects of innovation efforts (Schroeder *et al*., 2002).[1] Given the complexities of linkages between innovation and efficiency, the empirical evidence is mixed, and some studied – based on administrative theories (Zorzo *et al*., 2017) – document a trade-off between them.

Departing from these literature streams, we bring new evidence on this topic by employing the economic efficiency perspective to the extant literature. Consequently, we would like to investigate whether being financially constrained and undertaking innovation exert an effect on firms profit efficiency, by formulating the following predictions:

H1: *Binding finance constraints might exert a positive effect on firms efficiency, since debt constrained firms – in order to reduce their risk of failure – have an incentive to improve profit efficiency*.

H2: *Undertaking innovation activities might improve profit efficiency, since innovation efforts enable firms to offer high added value products and services, to charge higher prices and to improve their margin of profitability*.

[1] Another bulk of literature investigates on the effects that radical innovation might have on the economic performance of incumbent enterprises (Hill and Rothaermel, 2003; Wessel and Christensen 2012; Ansari *et al*., 2016). This literature highlights that a radical technological innovation might challenge established incumbent businesses eliciting a decline in their performance.

Our main contributions move along the following three dimensions. Firstly, our investigation fills the gap in the scant literature on the link between profit efficiency and innovation and sheds additional light on the link between financial constraints and profit efficiency.

Secondly, we jointly test whether innovation efforts and lessened financial constraints exert a significant effect on firms' efficiency. In particular, we enrich our understanding on firms' performance by adopting the stochastic frontier approach (SFA) to estimate profits functions and to obtain efficiency scores of European firms. The SFA is one of the mostly employed methods to estimate frontiers (production, profit, cost, revenues) and it allows to disentangle the distance from the best practice into two components, i.e. the random error and the inefficiency component (Kumbhakar and Lovell, 2000; Coelli *et al*., 2005). One of the advantages of the frontier approach is that it does not require firms to be fully efficient. Most importantly, it let us to retrieve a pure measure of efficiency that is a key component of productivity.[2] In this respect, the SFA allows to use a richer set of information in terms of time/firm dimension compared to other measures of productivity, which require only two points in time.

Thirdly, we pioneer the use of a novel dataset that merges survey-based data derived from the ECB Survey on access to finance for enterprises (SAFE) with balance sheet information – from AMADEUS by Bureau van Dijk (BvD). From the former we retrieve harmonized and homogeneous information on several aspects of financial constraints and innovation for a large set of European countries. The latter allows us to define output and input variables to be included in the production frontier and all firm-level information useful to pursue our research trajectory (e.g. leverage compositions, cash holding, inventories, sales and turnover).

This unique dataset enables us to rely on different indicators of financial constraints and innovation activities. We use both perceived and objective indicators of financial constraints based on the qualitative responses of surveyed firms. Following the contribution of Fazzari *et al*. (1988), which showed that firms depending on cash flow to finance their investments can be deemed financially constrained, we use the cash flow as an additional proxy for financial constraints. As for innovation activities, we employ direct measures of product innovation activity stated by the interviewed firms.

To take into account the different technologies and production functions across sectors, we estimate different frontiers for two main productive sectors: Industry and Services. Additionally, we complement our analysis with the Eurostat classification on high-technology industry and knowledge-intensive services in a similar fashion to Baum *et al*. (2017). The use of this further disaggregation allows us to exploit a sectoral heterogeneity which might be particularly relevant in our investigation.

[2] See Coelli *et al.* (2005) for details on how some productivity measures can be decomposed into efficiency change and technical change.

In fact, the high-technology/knowledge-intensive companies in the manufacturing and services turn to be more similar to each other than highly technology/knowledge-intensive and low technology/knowledge intensive within the two sectors.

Based on a variety of model specifications we document that innovation has an important impact on firm efficiency but only for firms in specific sectors. Specifically for high-technology and knowledge-intensive companies, product innovation has a strong positive impact on the profit efficiency, while for low technology and knowledge-intensive companies investments for product innovations seem to negatively affect firms' efficiency. Additionally, bearing in mind that policymakers and economists generally agree that well-functioning financial institutions and markets contribute to economic growth, we provide evidence that, in the presence of market failure, financial constraints induce firms to improve efficiency across sectors.

The rest of the paper is organized as follows. In the next Section we present the methodological issues, and we describe the firm-level database as well as the model used to test our hypotheses. Empirical results are presented in Section 3, while the last Section concludes.

2. Empirical setting

2.1 Stochastic Frontier Approach

In the previous section we introduced the theoretical reasoning of why the presence of financing constraints and the innovation efforts of firms may have a positive impact on profit efficiency. To test these hypotheses, we estimate the profit functions by employing the SFA, which is a stochastic method that allows companies to be distant from the frontier also for randomness (Aigner *et al*., 1977; Meeusen and van Den Broeck, 1977).[3] The SFA is also a parametric method, which means that it assigns a distribution function to the stochastic component of the model and, thus, allows making inference. In our analysis we make use of the specification introduced by Battese and Coelli (1995), which permits the simultaneous estimation of the parameters of the stochastic frontier and the inefficiency model, given appropriate distributional assumptions associated with panel data. This approach improves, in terms of consistency, previous modelling based on two steps.[4]

[3] The SFA differs from the Data Envelopment Analysis (DEA), which assumes that the distance from the frontier is entirely due to inefficiency.

[4] In the two-step approach, one firstly estimates inefficiency using a frontier and, secondly, uses the estimated efficiency-score as the dependent variable in subsequent regression (Greene, 1993). As shown by Lensink and Meesters (2014) and Wang and Schmidt (2002), the two-step approach suffers from the fact that the inefficiency is assumed to be identically and independently distributed in the main frontier equation, while it depends on other variables in the inefficiency equation.

We estimate a two-inputs-one-output model described by the following function $F_p(.)$, which indicates the profit obtainable from producing y at input price w.

$$Profit_{it} = F_p(y,w)e^{v_p}e^{-u_p} \qquad [1]$$

Eq. [1] is an alternative profit function since it depends on inputs and output, whereas actual profits depend on the prices of outputs. It uses the same variables as for a cost function, implying that output-prices are free to vary (Huizinga *et al.*, 2001). Exhaustive discussions on alternative versus traditional profit efficiency are in Berger and Mester (1997) and Vander-Vennet (2002).

From eq. [1], profit efficiency (PE) is the ratio between the observed firms' profit and the maximum level of profit achievable in case of full efficiency:

$$PE = \frac{F_p(y,w)e^{v_p}e^{-u_p}}{F_p(y,w)e^{v_p}} = e^{-u_p} \qquad [2]$$

We use the Translog function to model the form of frontiers, which satisfies the assumptions of non-negativity, concavity and linear homogeneity (Kumbhakar and Lovell, 2000). After taking into account the constraint of homogeneity in relation to input-prices (which requires the sum to one of the input price elasticities), the profit frontier in the log-linear form is as follows:

$$\log\left(\frac{Profit}{w_k}\right) = \beta_0 + \beta_1 \log y + \delta_1 \log\frac{w_l}{w_k} + \frac{1}{2}\left[\beta_2(\log y)^2 + \delta_2\left(\log\frac{w_l}{w_k}\right)^2\right]$$
$$+\alpha(\log y)\left(\log\frac{w_l}{w_k}\right) + v - u \qquad [3]$$

where the dependent variable is firms' profit, expressed as $\log\left(\frac{Profit}{w_k}\right)$. As in Berger and Mester (1997), Bonin *et al.* (2005), Fitzpatrick and McQuinn (2008), Huizinga *et al.* (2001) and Maudos *et al.* (2002), we transform profits by adding the absolute value of minimum profit plus one to actual profits. This ensures that $\log(Profit) = \log\left[\pi + |\pi^{min}| + 1\right]$ is defined in $[0, +\infty)$. Additionally, y represents the output and is equal to the operating revenues; w_l is the cost of labor, w_k is the cost of capital, measured as the cost of fixed asset; α, β and δ are the parameters to be estimated; v is the random error; u is the inefficiency. In the profit frontier, the inefficiency tends to reduce the profit, thus the composite error is equal to (v-u).

Our dependent variable is the natural logarithm of the value added over the cost of fixed asset. We choose the value added to proxy profit as it includes both revenues and costs information. As for the inputs price, we measure the cost of labor as the ratio between the personnel expenses and the number of employees, and the cost of capital as the ratio between the depreciation and total amount of fixed assets.

In the frontiers, we take account of the cross-country heterogeneity by including a dummy for each country in our models. These dummy variables guarantee that the efficiency scores are net of any geographical and institutional fixed effect. We consider the possibility of different shifts in the frontier for different size, by introducing a dummy for each group of firms (micro, small and medium).[5]

To take into account the different technologies and production functions across sectors, we estimate different frontiers for two productive sectors: Industry and Services. Additionally, we use the Eurostat classification on high-technology industry and knowledge-intensive services to define five main sub-sectors: high- medium- and low-technology firms (HT, MT and LT, respectively) within manufacturing, and knowledge-intensive (KIS) and less knowledge intensive (less-KIS) companies within Services.[6]

Finally, we assume that v_{it} is normally distributed with mean zero and u_{it} is distributed as a truncated normal. Again, v_{it} and u_{it} are independently and identically distributed:

$$v_{it} \sim iidN\,(0, \sigma_v^2) \tag{4}$$

$$u_{it} \sim N^{+}\,(\boldsymbol{z}'\boldsymbol{\eta}, \sigma_u^2) \tag{5}$$

where $\boldsymbol{z}'\boldsymbol{\eta}$ is the linear predictor of inefficiency. The inefficiency component is specified as:

$$u_{it} = \sum_{k=1}^{K} \eta_k z_{kit} + e_{it} \tag{6}$$

[5] Micro and small firms have less than 9 and between 10 and 49 employees, respectively; medium firms have between 50 and 249 employees; large enterprises have 250 or more employees. In our analysis large firms are the controlling group.

[6] See Eurostat: https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf.
Based on NACE Rev. 2 at 2-digit level Eurostat has compiled a classification of 12 sectors and subsectors according to their degree of technology and knowledge intensity. In the paper we use the main 5 sectors.

where z_{kit} represents the k-th variable that affects inefficiency of the i-th firm; with $k = 1, ..., K$; t is time and e_{it} the random component. In addition, the inequality $e > - \boldsymbol{z}'\boldsymbol{\eta}$ ensures the non-negativity of u. Specifically, we employ the following model:

$$u_{it} = F\left(Financial\ constraints_{it}, Innovation_{it}, Performance_{it}, Business\ cycle_{jt}\right) \qquad [7]$$

where i indicates the firm, t the time (*wave*), and j the country.

Efficiency is time-varying, ensuring a change in relative ranking among enterprises. In other words, this accommodates the case where an initially inefficient firm becomes more efficient over time.

To test the effect of the determinants of firms' efficiency, we simultaneously estimate equations (3) and (7) and we employ the following covariates:

i) *Financial constraints*$_{it}$ includes a set of variables able to capture firms' experience in their access to finance. We consider separately three different proxies of financial constraints. First, we use the ratio between cash flow and total assets (*Cash flow/Total assets*$_{it}$). This indicator has been employed in literature as a proxy of financial constraints (Fazzari *et al*., 1988; Guariglia and Liu, 2014; Sasidharan *et al*., 2015). In this view, the dependence to internal finance, represents a particularly binding constraint for firms to finance investment. We are aware of the criticism of the subsequent literature on the use of this indicator (starting by Kaplan and Zingales, 1995, and recently summarized in Farre-Mensa and Ljungqvist, 2016). For this reason, we turn to the information derived from the survey to define financial constrained firms.

Our second variable is *Problem of Finance*$_{it}$, which is a dummy equal to one if the firm reported that access to finance represents the most relevant problem among a set of other problems (competition, finding customers, costs of production or labour, availability of skilled staffs and business regulation), and 0 otherwise. This variable captures the perception of potential financing constraints which differs from our third indicator – *Finance obstacles*$_{it}$ – which is an "objective" measure of credit constraints, always derived from the survey. This dummy variable indicates firms as financially constrained if they report that: 1) their loan applications were rejected; 2) only a limited amount of credit was granted; 3) they themselves rejected the loan offer because the borrowing costs were too high or 4) they did not apply for a loan for fear of rejection (i.e. discouraged borrowers). The indicator is equal to one if at least one of the above conditions (1-4) is verified, and 0 otherwise.

As shown in Ferrando and Mulier (2015), firms that self-report finance as the largest obstacle for their business activity have different characteristics compared with financially constrained firms. For instance, the authors find that more profitable firms are less likely to face actual financing constraints, while firms are more likely to perceive access to finance problematic when they have more debt with short term maturity. For this reason we consider both indicators in our analysis.

ii) $Innovation_{it}$: is a dummy equal to one if the firm declares in the survey to have undertaken product innovation, and 0 otherwise.[7] By construction of the survey, the decision to report an innovation stays completely with the surveyed firms and it is not possible to control the degree of innovation imbedded in the products that firms have developed. This caveat has to be taken into consideration in the analysis, even though there are no reasons to think that firms might wrongly respond to the question either to overstate or downstate their innovation capacity. Additionally, the survey also contains information about the types of innovation introduced by the firms (product, process, organizational and marketing), which allow to precisely capture product innovation. For robustness check we use also the survey information on the use of finance to develop or launch new products and services, which might be considered as a proxy of R&D expenditures.[8]

iii) In addition, we use some firm-varying covariates describing firms' market and debt conditions, $Performance_{it}$. To capture the change in profitability – in a similar fashion to Srairi (2010) and to Luo *et al*. (2016) – we rely on two alternative measures. The first is $Profit\ margin_{it}$, defined as net income divided by sales and the second $Profit\ up_{it}$ *which* is a dummy equal to one if the firm has experienced an increase in profit in the past six months, and 0 otherwise.[9] We proxy the information on the change in firm debt conditions using the dummy $Leverage\ up_{it}$ which is equal to one if the firm has experienced an increase in the ratio debt/assets in the past six months, and 0 otherwise. In some specifications, we consider also the maturity structure of indebtedness and the debt burden in terms of interest expenses (Vermoesen *et al*., 2013). Both variables are derived from the financial statements as explained in detail in the next section.

[7] The information on this variable (question *Q*1 in the survey) is provided by SAFE every second wave, and refers to the previous 12 months, i.e. two waves. As the SAFE survey is conducted every six months, in order to restore this information at the wave round, we replicate this data for firms present on consecutive waves.

[8] This is question *Q*6A in the survey. We construct a second variable for innovation: $Financing\ product\ innovation_{it}$ which is a dummy equal to one if the firm declares to have used finance to develop or launch new products and services, and 0 otherwise.

[9] In the empirical analysis we use this proxy when the measure of finance constraints is the Cash flow/Total assets ratio because of the high correlation with the profit margin ratio, see Table 2.

iv) Finally, to take into account the effect of business cycle, we use the *Real GDP growth*$_{jt}$ rate. As in Ferrando *et al*. (2017) for this macro variable, we use averages of quarterly data for each survey round.

2.2. Data and variables

In order to test our hypotheses, we rely on a novel dataset that merges survey-based data derived from the ECB SAFE with balance sheet information – from BvD AMADEUS. SAFE gathers information about access to finance for non-financial enterprises in the European Union. It is an on-going survey conducted on behalf of the European Commission and the European Central Bank (ECB) every 6 months since 2009. The sample of interviewed firms is randomly selected from the Dun and Bradstreet database and it is stratified by firm-size class, economic activity and country. The sample size for each economic activity is chosen to guarantee satisfactory representation across the four largest industries: Industry, Construction, Trade and Services. Furthermore, the sample sizes are selected on the basis of representation at the country level. The replies are voluntary and the interviews are mostly conducted by telephone (using computer-assisted telephone interviewing or CATI). Around 10% of respondents fill the on-line questionnaire. The specific individual that is surveyed in each firm is a top-level executive and the questionnaire is administered in the local language. Sample replies are anonymous and statistical disclosure procedures are applied to preserve the anonymity in the micro dataset.[10] Between 8,000 and 15,000 firms were interviewed in each wave.

Our investigation is based on firms belonging to the following eight European countries (Austria, Belgium, France, Finland, Germany, Italy, Portugal and Spain) observed from wave 1 (second part of 2009) until wave 17 (first part of 2017). We augmented the responses of firms that participated in the survey rounds with detailed balance sheet and profit & loss information available in BvD AMADEUS between 2008 and 2016.[11]

This combined dataset has the major advantage that it allows us: first to retrieve harmonized and homogeneous information on several aspects of financial constraints and innovation from the survey dimension of the dataset. Second, we can define output and input variables to be included in the production frontier and all firm-level information useful to pursue our research trajectory (e.g. leverage compositions and profitability measures).

[10] For an overview of the methodology followed on the set-up of the survey see https://www.ecb.europa.eu/stats/pdf/surveys/sme/methodological_information_survey_and_user_guide.pdf?ecdc7494b2abc88048ce44465a60be2b

[11] The selection of those countries is driven by the availability of the data after the merge of surveyed firms in SAFE with the financial statements in the dataset from BvD AMADEUS.

To start, we focus our analysis on firms belonging to Industry and Services.[12] Our choice is driven by the following considerations. *i*) They are the largest sectors (Industry accounts for about 19% of European GDP, and Services account for about two thirds of European value added (Eurostat data, 2016). *ii*) They have displayed divergent trends in recent years in terms of shares of value added to GDP with a declining trend for Industry and an increasing one for Services (Stehrer *et al*., 2015). *iii*) The two sectors differ also for their efficient allocation of resources as shown by the allocative efficiency index, which is particularly low for the Services sector (European Commission, 2013). A sub-optimal resource allocation constrains the productivity of the Services sector and hampers its competitiveness.

Additionally, to take into account the heterogeneity derived from the different technological characteristics of the firms, we use the classification provided by Eurostat of high-, medium-, low-technology industries, and knowledge-intensive and less knowledge-intensive services.

Our samples include 15,699 firm-wave observations for Industry and 13,943 for Services. Specifically, Table 1 displays the variables used in defining the frontiers (Panel A) and the determinants of efficiency (Panel B) for both sectors of activities. All balance sheet data are deflated using HICP index. As the two sets of observations are very similar in the two specifications, we focus on the first one related to the profit function estimations depicted in panel A. The majority of firms in the sample are SMEs by construction of the survey.[13] On average firms have 200 employees, mainly due to very large companies in the dataset. Among SMEs, the average number of employees per firms is 66 for Industry and 44 for Services. 14% of firms in Industry and 15% in Services perceived access to finance as a major problem. A slightly lower percentage of firms (around 11%) are financially constrained according to the objective indicator *Finance obstacles.*

Regarding the innovative activity, around 46% and 31% of firms have indicated that they introduced product innovation in the previous six months in Industry and Services, respectively.

- INSERT TABLE 1 -

Turning to the financial position, the average firm in our sample is profitable with a profit margin of around 1.4% in both sectors, although looking at the distribution we see that at least 10% of

[12] We use the 2-digit NACE classification used in the survey to define the two sectors. Industry includes manufacturing, mining, electricity, gas and water supply, while Services include construction, wholesale and retail trade, transport, accommodation, food services and other services to business or persons. We exclude public administration, financial and insurance services.

[13] Albeit the main focus of SAFE is on SMEs, the survey also provides information on large firms. As for Services 12% of our sample are large enterprises. In the case of Industry they are 16%.

all firms in our sample are reporting losses. On average, firms in our sample are able to generate internal funds (6.6% and 7.5% of total assets for Industry and Services, respectively). At the same time, *Leverage up* is indicating that at least 20% of them are reporting increasing debt to total assets. Although not used directly in the regressions, we have constructed some additional financial ratios to quantify better the financial conditions of firms in the sample, which are included in Table 1. In particular, we present the financial leverage and the return on equity (ROE).[14] From panel B, we can see that the representative firm has financial debt which is around 21-22% of total assets. The return on equity ratios are 2.9 % for Industry and 3.2% for Services. These ratios, although relatively low, show some efficiency by firms in using their equity. It also emerges that the use of bank loans and credit lines are more relevant for firms operating in Industry than in Services (38% and 46% of firms operating in the Industry sector use bank loans and credit lines, respectively while the percentages are 31% and 39% for firms operating in Services).[15]

As for the production factors in Panel A, labor costs are on average lower for firms in the Industry sector than for those in the Services sector (49.3 and 52.9 thousand euros per employee, respectively). At the same time capital costs are also much lower for the first group of firms (27% of fixed assets versus 46%) and operating revenues much higher so that firms in Industry are economically more profitable than those in Services (13.9 and 7.8 thousand euros, respectively).

Interesting insights come from Figures 1 and 2, where we plot the dynamics of the main regressors used in our estimated models for Industry and Services, respectively. Starting from the upper left panel, we report the evolution over time of the cash flow ratio. In both sectors, this is characterised by the double-dip following the financial crisis of 2009 and then the economic recession which hit many countries in the euro area during the sovereign debt crisis of 2012. In these two time spans, firms show a sharp decline in their economic activity and in their ability to generate internal funds. Our sample covers also the recovery period characterised by a steady increase in the cash flow ratio. The vertical line – in correspondence of the 7th wave – corresponds to the announcement of the Outright Monetary Transaction (OMT) Program by the European Central Bank in summer 2012 aimed at safeguarding an appropriate monetary policy transmission and the singleness of monetary policy. As documented in Rostagno *et al*. (2019), financial markets reacted immediately and by the end of 2013,

[14] The financial leverage is defined as the ratio of short and long term debt, excluding trade credit and provisions, to total assets while the return on equity (ROE) is the amount of net profit earned as a percentage of shareholders' equity.

[15] The variables *Use bank loans*, *Use credit lines* and *Use bank credit* capture firm experience in the use of different financing sources. They are dummy variables equal to 1 if the related financing source is used by the reporting firm and 0 otherwise. The first two variables refer to a single financing source, whereas, in order to have a broader measure of the use of bank credit, we construct the dummy *Use bank credit*, which is equal to 1 if the firm declares to have used at least one bank financing source (bank loans and/or credit lines) in the last six months, and 0 otherwise.

even though the ECB did not purchase a single government bond through the OMT Program, government bond yields had returned to pre-crisis levels. The improvements in financial markets passed through into credit conditions for the real economy. As documented in our data, the period just after the OMT announcement represented a clear turning point in the perceived financial obstacles reported by the surveyed firms in both sectors (upper panel on the right-hand side of Figures 1 and 2).[16] A similar pattern is documented for the more objective indicator of financial constraints (lower panel on the left-hand side of Figures 1 and 2), though it seems that firms were more credit constrained in the second part of 2014 than what they perceived. As a final chart, we display the percentages of firms that have introduced a product innovation. The information starts only in the second half of 2012, when the survey started to collect this information. Though the dynamics is similar across two sectors, a higher percentage of firms in the Industry sector signalled to have introduced a product innovation.

- INSERT FIGURE 1 AND FIGURE 2 -

Table A1 in the Appendix reports the correlation matrix of the variable used in the inefficiency equation. Most of the variables report a statistically significant correlation, though in most cases the magnitude is small. The correlation is negative between the different measures of profitability and the financial constraints indicators, while it is positive between profitability and innovation. Our measure of leverage is positively correlated with financial constraints and innovation. As expected, there is a very high correlation between the ratios of cash flow and profit margin. As explained in the previous section, we take care of this in the empirical analysis by not using these two indicators together.

3. Econometric results

3.1 The impact of innovation and finance constraints

In this Section we discuss the results of the maximum likelihood estimations of the profit functions for both Industry and Services. Following the approach proposed by Battese and Coelli (1995), the coefficients are obtained by simultaneous estimates of the profit efficiency frontier (equation 3) and the inefficiency term, expressed as a function of a set of explanatory variables (equation 7).

[16] See also Ferrando *et al*. (2017) for an analysis of the impact of the announcement of the ECB's OMT Program on small firms' access to finance.

The estimation of a common frontier is the method most widely used to compare the performances of firms across different countries. We impose a cross-equation equality restriction on the parameters of each sector's profit frontier in order to obtain results which are not influenced by the heterogeneity of sector's technology.[17] Additionally, we add country-specific and time variables to the profit function specifications to take into account the impact of those types of heterogeneity on the inefficiency scores.

The results presented in Tables 2 and 3 show the appropriateness of the Translog specification used in the analysis. In fact, it turns out that most of the second-order terms parameter estimates of the profit function are significant. In addition, the high value of the estimation of the γ parameters, reflecting the importance of the inefficiency effects, strongly advocates the use of the stochastic frontier production function rather the standard OLS method. Finally, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are used to provide some models diagnostics (Burnham and Anderson, 2004).[18]

In Tables 2 and 3 we display several specifications (columns 1-7) of our basic model which differ for the progressive and alternative inclusion of the *z*-variables of the inefficiency equation.

Specifically, in specifications 1-4 we introduce one by one the three proxies for financial constraints – *Cash flow ratio*, *Problem of Finance, Finance obstacles* – and the variable *Innovation*. In this way, we are able to exclude the possibility that our findings are driven by the contemporaneous presence of those variables. In columns 5-7 we jointly use the financial constraints proxies and the variable innovation. In the various specifications we take care of the high correlation between the cash flow ratio and the profit margin. Hence when we employ the continuous variable *Cash flow ratio* we use the dummy *Profit up* as our preferred profitability measure. When the financial constraints indicators are those derived from the survey (*Problem of finance* and *Finance obstacles),* we use the *Profit margin*, retrieved from balance sheet data.

Starting with the Industry sector (Table 2), all three measures of firms' external financial constraints display a negative and significant coefficient. In the context of the Battese and Coelli (1995) model, the negative sign of the coefficients implies that firms with tighter financial constraints are forced to be more efficient. When the availability of external finance decreases, firms tend to reduce inefficiency in order to counter the potential adverse impact of financial constraints on their profitability. These findings provide support to our prediction (H1) and are in line with previous

[17] We will expand on the heterogeneity across sectors in Section 3.3 looking at sector disaggregation based on the technology and knowledge intensity.

[18] AIC is equal to [2k-2Log-likelihood], where k is the number of estimated parameters; BIC is equal to [ln(N. obs) k-2 Log-likelihood].

studies based on different countries and sample periods (Nickell and Nicolitsas, 1999; Sena, 2006; Maietta and Sena, 2010; Bhaumik *et al*., 2012).

Interestingly, we also find a negative and significant coefficient for the variable *Innovation*.[19] This indicates that the efforts of firms to develop new products or services in order to attain a strategic advantage over competitors produce some leverage on revenues. This evidence corroborates the prediction of our hypothesis (H2).[20] Our analysis also shows the relevance of the performance indicators (profit and leverage). In all specifications, the two alternative measures of profit (*Profit up* and *Profit margins*) and leverage (*Leverage up*) display a negative and significant coefficient, suggesting that the increase in profitability and leverage have a positive effect on efficiency. Finally, the *Real GDP* growth, when strongly significant, displays the expected negative sign.

- INSERT TABLE 2 -

The results for firms operating in the Services sector are displayed in Table 3. Remarkably, some similarities emerge with the analysis performed for the Industry firms as the financial obstacles and the firm performance indicators indicate the positive effect exerted by those variables on efficiency (negative coefficients). By contrast, and differently from the Industry case, the variable *Innovation* is not statistically significant in most specifications, with the exception of the last one (Column 7). This general outcome may be explained by the fact that the Services sector is traditionally considered non-tradeable and therefore less exposed to the competition. Hence, the pressure for firms to develop and launch new products and services in the market might be less cogent. Indeed, in the literature it has been found that the incentive to increase efficiency is higher in sectors where competition is high (Hay and Liu, 1997). To corroborate this evidence we have performed an additional test for the Services sector using the variable *Problem of competition*. Firms use this reply in the survey to signal whether competition is a problem in their business activity. Interestingly, firms in services are those reporting less often that this is a problem for them. When we control for the impact of competition, the results confirm our previous evidence.

Additionally, the business cycle seems to have a different impact compared to the Industry sector. The *Real GDP growth* turns to be significant and positive in almost all specifications (meaning a negative effect on the efficiency), which confirms the divergence in the dynamics of the value added

[19] The variable *Innovation* is available in SAFE from the 8th wave onwards (second half of 2012). Therefore, the use of this variable in columns (4-7) leads to a drop in the number of observations.
[20] Additionally we tried the interaction terms between *Innovation* and the indicators of financial constraints. Estimates (available upon request) did not provide conclusive results on an additional effect.

as reported in the aggregate data (Stehrer *et al*., 2015). To corroborate these results, we have rerun the equations by adding country*time fixed effects into the frontier equation and dropped the real GDP growth in the inefficiency equation. This is an alternative way to capture unobservable changes in the economic sentiment which can have an effect on the level of innovation and investments in intangible assets. The main results on the variables of interests do not change.

- INSERT TABLE 3-

Finally, to give a bit the flavour of the heterogeneity in our sample we focus on Model 5, where the resulting mean profit efficiency is equal to 67.7% for Industry. Untabulated profit efficiency scores (PE) show that across countries, Finnish firms seems to be the most efficient in our sample (71.3%) while Austrian firms display the lowest value of mean profit efficiency (64.1%). In the Services sector, our analysis confirms that firms located in Finland seem to be the most efficient (70%) and Spanish firms present the lowest performance (62.4%), while the overall mean PE is equal to 65%. Across firm size, we find a positive relation between efficiency and size. In fact, micro firms achieve a mean efficiency score of about 56% and 59% for Industry and Services, respectively, while for large firms the mean PE value is much higher in both sectors (about 73%).

As an additional robustness check, we re-estimate the models in column (7) of Tables 2 and 3 by using the second measure of innovation, the dummy *Financing product innovation*. The resulting estimates, not reported here for the sake of brevity, turn out to be consistent with the evidence provided earlier. Furthermore, to address potential endogeneity issues related to the link between efficiency and innovation, we implemented the instrumental variable approach proposed by Karakaplan and Kutlu (2017). By using as an instrument R&D expenses as percentage of GDP by sector of activity, this approach allows us to test the endogeneity bias in the stochastic frontier estimation in both the frontier and efficiency determinants equations. The results rule out any evidence of endogeneity referred to *Product innovation*.[21]

3.2 Sectoral heterogeneity: high- and low-tech sectors

To take further into consideration the sectoral heterogeneity characterizing the firms of our sample, we disaggregated Industry and Service sectors according to firms' technological and knowledge-intensity. Starting from the Eurostat classification on technological and knowledge

[21] Results are available upon request.

intensity, we collapse the sectors into two main groups: High-Tech and Low-Tech sectors. In the first group we include high-technology industries and knowledge-intensive services (HT and KIS) and in the second one medium-low and low-technology industries and less knowledge intensive (MT, LT and less-KIS).

Our assumption is that HT companies in Industry and KIS companies in Services are more similar to each other than highly knowledge-intensive and low technology/knowledge intensive within the two sectors.

The results of the simultaneous estimation of equation (3) and several specifications of equation (7) for High-Tech and Low-Tech sectors are displayed in Table 4. Specifically, we report the results for High-Tech in columns 1-3, and for Low-Tech sectors in columns 4-6.

- INSERT TABLE 4-

The results are noteworthy. First the variables accounting for the financial constrains turn to be significant with the negative sign in all specifications for Low-Tech firms. Conversely, this effect disappears for High-Tech businesses with the exception of the cash flow ratio, which displays the negative sign indicating that firms using internal sources are forced to be more efficient. Secondly, our evidence shows that for all three specifications of the High-Tech sector the variable *Innovation* displays always a negative sign, indicating that this type of activity produces positive effect on the profit efficiency. By contrast, innovation efforts seem to hamper profit efficiency among Low-Tech as the estimated coefficient is positive in all three specifications. This evidence indicates that investments in product innovation for High-Tech companies imply complementing different tasks such as information technologies, which in turns produce efficiency gains. In the case of Low-Tech companies it seems that the business activities needed to introduce new products might divert funds and efforts that could be otherwise used in a more efficient way. However, when financial constraints are binding, Low-Tech firms are induced to be more efficient to enhance their profitability than High-Tech firms. Noticeably, the signs of all the other inefficient determinants are stable across the High-Tech and Low-Tech disaggregation.

To further exploit the sectoral disaggregation of our dataset, we have estimated our model by disaggregating the sectors into HT, MT and LT for Industry and for KIS and less-KIS for Services, in a similar fashion to Baum *et al*. (2017). In the Appendix, Table A2 reports the results with the *Cash flow ratio* (like column 5 in Tables 2 and 3). Similar results are obtained when we use the other indicators of financial constraints. Noticeably, the variable innovation displays the expected negative sign for HT industry and KIS Services. This reinforces once more our hypothesis that the two sectors share more common characteristics in terms of the impact of innovation on efficiency than the other subgroups.

Consistently with the evidence reported in Section 3.1, untabulated results show that Finnish firms achieve the best performance in terms of efficiency, while firms located in Austria and Spain show the lowest PE values. Also, the positive trend of PE with increasing size is confirmed for both groups High-Tech and Low-Tech.

3.3 Robustness analysis: a focus on micro-small firms

By looking at our sample composition, summary statistics show that close to 40 percent of the industrial companies and almost 60 percent of the service companies are classified as micro and small (see Table 1). Previous studies have shown that firms' size matters on the decision to innovate (see among others, Leal-Rodríguez *et al.*, 2015; Baumann and Kritikos, 2016). As for innovation, two opposite perspectives are recalled here. According to the Schumpeterian point of view (Schumpeter 1942; Karlsson and Olsson, 1998) large firms have an advantage to innovate *vis à vis* smaller companies as innovation requires effort, long-time investment, know-how and resources that often small firms cannot afford. On the opposite, other studies show that smaller-sized firms tend to display more innovative and efficient efforts than large firms in order to survive (Cohen and Klepper 1996; Laforet, 2008; De Jong and Marsili, 2006; Laforet, 2013; Baumann and Kritikos, 2016).

To address the issue we re-estimate our model specifications on sub-samples of micro (1-9 employees) and small (10-49 employees) firms for a total of 2,876 and 3,626 wave-firm observations for Industry and Services, respectively. Results are displayed in Table 5 where we report only the *z*-variables of the several inefficiency term specifications. As far as Industry is concerned, while the sign and the significance of the financial constraints covariates are consistent with the previous analysis, the variable product innovation turns to be not significant. We read these inconclusive results as a signal that we should investigate the impact of innovation on small-sized firms by focusing more on their innovative characteristics. By contrast, no relevant differences emerge for the micro-small firms compared to the full sample in the Services sector.

Indeed, the sector disaggregation based on the technology and knowledge intensity brings more clear-cut findings. In detail, we observe that for the micro-small High-Tech enterprises product innovation matters in reducing firm inefficiency, while for Low-Tech firms the innovation efforts are negligible or they could be even counter-productive as they induce an increase of inefficiency. Once again these results are largely consistent with the findings on the full sample, on the similarity between technological and knowledge-intensive companies are indeed more similar to each other independently from size.

- INSERT TABLE 5-

4. Conclusions

This paper contributes to the literature that investigates the interplay between efficiency, innovation and firms' access to finance. Despite the policy relevance of this topic, the fundamental assumptions underlying it have remained largely unexplored. Indeed, the related literature has mainly focused on the role of financial constraints and innovation on productivity separately, yet these studies do not address the direct link between innovation and profit efficiency and the effect that a limited access to credit may exert on profit efficiency.

We fill this gap by employing the economic efficiency perspective to the existent literature. To the best of our knowledge, no previous work took into account both the effects that innovation and credit access limitations may have on profit efficiency within the same framework. To accomplish such a task, we pioneer the use of a novel dataset that merges survey-based data derived from the ECB Survey on access to finance for enterprises (SAFE) with balance sheet information – from BvD AMADEUS. This allows us to exploit the heterogeneity across firms' financial and financing positions.

Furthermore, in order to take into account the different technologies and production functions across sectors, we estimated different frontiers for two main productive sectors: Industry and Services. In addition, we investigated the sectoral heterogeneity based on the technological and knowledge intensity. The empirical analysis confirms the hypothesis that technological and knowledge-intensive companies in the manufacturing and service sectors are more similar to each other than highly and low technological and knowledge-intensive within each sector.

Our main findings support the prediction (H1) according to which firms that perceived difficulties in accessing external finance, or that are objectively deemed as financially constrained, have an incentive to improve efficiency to reduce their risk of failure and to guarantee positive profits, independently from the macro sector disaggregation (Industry and Services). This outcome seems to be consistent with previous literature (Sena, 2006). Our analysis also documents that when financial constraints are binding, Low-Tech firms are induced to be more efficient to enhance their profitability than High-Tech firms.

Consistently with our hypothesis (H2), we show that firms which undertook product innovation have a higher likelihood to improve efficiency but results differ across sectors. The evidence is robust for firms in the Industry sector, and only weakly present for firms belonging to Services. We also find that product innovation matters for increasing profit efficiency for high-technology and knowledge-intensive companies, while for low-technology and less knowledge-intensive firms innovation efforts negatively affect profit efficiency.

Finally, our evidence on sub-samples of micro- and small-firms largely confirms the findings on the full sample. Specifically, we show that micro and small High Tech firms are able to turn innovation and knowledge into productivity gains, while for low-technology and less-KIS companies innovation does not produce leverage on revenues. This supports the fact that the different sectoral disaggregations provided in our analysis are indeed relevant for detecting additional firm heterogeneity independently from firms' size.

The implication of this result is not negligible. Fostering innovation and growth opportunities for enterprises is particularly relevant in times of economic slowdown and financial distress. Recommendations for public policy to encourage long-term investment in innovation and to reduce conducts which particularly penalize enterprises when investing in R&D would be another outcome of our investigation. Hence, our results give support to the line of firm-level policy interventions directly aimed at mitigating the underinvestment in R&D in Europe which take into account firm heterogeneity across technology and knowledge intensity sectors. Though not explicitly analysed in this paper, our results could help to better understand the link between innovation, financial constraints and efficiency, which goes beyond the idea that easier access to finance is the *panacea* to get higher profit efficiency. What seems more important is the support provided to businesses to be competitive by encouraging them to adopt new business models and innovative practices.

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Tables

Table 1. Descriptive statistics for profit functions and inefficiency equations

Panel A: Profit frontier	N. obs	Mean	Standard deviation	N. obs	Mean	Standard deviation
	INDUSTRY			SERVICES		
Added value♦	15,699	13,918	180,000	13,943	7,825	65,851
Operating revenues♦	15,699	50,767	580,000	13,943	22,018	260,000
Labour cost♦	15,699	49.292	392.130	13,943	52.850	368.600
Capital cost♦	15,699	0.274	2.926	13,943	0.458	9.049
log (added value/ cost fixed asset) ♦	15,699	9.985	2.012	13,943	9.066	2.271
log (operating revenues) ♦	15,699	9.135	1.815	13,943	7.876	1.930
log (labour cost)♦	15,699	5.548	1.186	13,943	5.394	1.449
Number of employees♣	15,699	201	1775	13,943	200	2869
Panel B: Inefficiency equation	**N. obs**	**Mean**	**Standard deviation**	**N. obs**	**Mean**	**Standard deviation**
Cash flow to total assets♦	15,699	0.066	0.086	13,943	0.075	0.121
Problem of finance♣	14,637	0.143	0.350	12,911	0.151	0.358
Finance obstacles♣	12,060	0.112	0.316	10,172	0.111	0.314
Innovation♣	7,279	0.458	0.498	5,864	0.314	0.464
Financing product innovation♣	7,312	0.209	0.406	6,372	0.131	0.338
Profit up♣	15,699	0.304	0.460	13,943	0.266	0.442
Profit margin♦	14,637	0.014	0.086	12,911	0.014	0.118
Leverage up♣	15,699	0.202	0.402	13,943	0.207	0.405
ROE♦	15,660	2.868	14.248	13,882	3.193	14.242
Financial leverage♦	14,989	0.216	0.193	12,715	0.228	0.232
Use bank loans♣	15,699	0.382	0.486	13,943	0.312	0.463
Use credit lines♣	15,699	0.457	0.498	13,943	0.387	0.487
Use bank credit♣	15,699	0.598	0.490	13,943	0.522	0.500
Real GDP growth	15,699	0.493	1.874	13,943	0.507	1.999
Micro♣	15,699	0.094	0.292	13,943	0.288	0.453
Small♣	15,699	0.294	0.456	13,943	0.306	0.461
Medium♣	15,699	0.456	0.498	13,943	0.290	0.454
Large♣	15,699	0.157	0.363	13,943	0.116	0.321

Source: our elaboration on data from SAFE & BvD AMADEUS. Legend: ♣ for variables retrieved from SAFE; ♦ for variables retrieved from BvD AMADEUS.

Table 2. Estimation of profit functions and inefficiency equations for the Industry sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Profit frontier							
Intercept	2.8468 ***	1.5268 ***	1.6836 ***	1.6183 ***	3.1480 ***	1.6476 ***	1.7311 ***
Log(Operating revenues)	0.0560 ***	0.3872 ***	0.3850 ***	0.4501 ***	0.0355	0.4388 ***	0.4331 ***
Log(wl/wk)	0.7620 ***	0.6205 ***	0.6462 ***	0.5188 ***	0.6889 ***	0.5198 ***	0.5186 ***
Log(Operating revenues)^2	0.0653 ***	0.0323 ***	0.0353 ***	0.0212 ***	0.0665 ***	0.0222 ***	0.0251 ***
Log(wl/wk)2	0.0471 ***	0.0494 ***	0.0542 ***	0.0633 ***	0.0655 ***	0.0631 ***	0.0704 ***
Log(Operating revenues*wl/wk)	-0.0208 ***	-0.0086 ***	-0.0152 ***	-0.0032	-0.0218 ***	-0.0033	-0.0093 **
Country Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inefficiency equation							
Cash flow/Total assets	-7.3045 ***				-7.7532 ***		
Problem of finance		-0.1816 ***				-0.1168 *	
Finance obstacles			-0.0816 *				-0.1291 ^
Innovation				-0.1331 ***	-0.1279 *	-0.1284 ***	-0.1175 **
Profit up	-0.1313 ***				-0.0999 *		
Profit margin		-3.9041 ***	-3.5086 ***	-3.4786 ***		-3.5652 ***	-3.4140 ***
Leverage up	-0.1751 ***	-0.0477	-0.0300	-0.1816 ***	-0.3989 ***	-0.1690 ***	-0.1426 **
Real GDP growth	-0.0296 **	-0.0493 ***	-0.0309 ***	0.0334	0.0206	0.0284	0.0486 *
σ^2	0.8360 ***	0.7099 ***	0.6477 ***	0.6918 ***	0.8896 ***	0.6974 ***	0.6621 ***
γ	0.6617 ***	0.6575 ***	0.6202 ***	0.6187 ***	0.6815 ***	0.6222 ***	0.5935 ***
N. obs	15,699	14,637	12,060	7,168	7,279	7,090	5,327

Log-likelihood	-15373	-13913	-11266	-6875	-7172	-6797	-5077
Mean PE	0.6778	0.6437	0.6543	0.6570	0.6771	0.6579	0.6658
SD	0.1416	0.1391	0.1315	0.1293	0.1415	0.1293	0.1239
Min	0.0052	0.0060	0.0073	0.0083	0.0046	0.0084	0.0095
Max	0.9474	0.9558	0.9657	0.9530	0.9415	0.9531	0.9487
k	37	37	37	31	32	32	32
AIC	30821	27899	22605	13812	14408	13658	10218
BIC	31104	28180	22879	14025	14629	13878	10428

Source: our elaboration on data from SAFE & BvD AMADEUS.

Significance levels: '***' 0.01, '**' 0.05, '*' 0.10 [^ 11%].
[a] $\sigma^2 = \sigma_u^2 + \sigma_v^2$; this is composed of the error variance, given by the sum of the variances of the two components.
[b] $\gamma = \frac{\sigma_u^2}{\sigma^2}$; the zero value of this parameter indicates that deviations from the frontier are only due to random error; while values close to one of the range entail that the distance from the border is due to inefficiency. This parameter, in the technique of Jondrow *et al*. (1982) is used to separate the component of inefficiency (JLMS technique).
Moreover, k is the number of estimated parameters; the statistics AIC and BIC are used for models diagnostics.
The econometric results are the simultaneous estimation of the following system of equations:

$$\begin{cases} \log Profit_{it} = \log F_p(y_{it}, w_{it}) + v_{it} - u_{it} \\ u_{it} = F(Financial\ constraints_{it}, Innovation_{it}, Performance_{it}, Business\ cycle_{jt}) \end{cases}$$

Table 3. Estimation of profit functions and inefficiency equations for the Services sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Profit frontier							
Intercept	0.0784	-0.8924 ***	-0.6279 ***	-0.7958 ***	0.2460	-0.8539 ***	-1.0440 ***
Log(Operating revenues)	0.7259 ***	0.8976 ***	0.9404 ***	0.8212 ***	0.6354 ***	0.8207 ***	0.8174 ***
Log(wl/wk)	0.8463 ***	0.7714 ***	0.7761 ***	0.8531 ***	0.9137 ***	0.8685 ***	0.9489 ***
Log(Operating revenues)^2	-0.0080 **	-0.0243 ***	-0.0232 ***	-0.0126 **	0.0024	-0.0117 **	-0.0038
Log(wl/wk)2	0.0055	0.0102 **	0.0144 ***	0.0081	0.0026	0.0067	0.0042
Log(Operating revenues*wl/wk)	-0.0156 ***	-0.0112 ***	-0.0169 ***	-0.0159 ***	-0.0175 ***	-0.0171 ***	-0.0264 ***
Country Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inefficiency equation							
Cash flow/Total assets	-4.090 ***				-4.1044 ***		
Problem of finance		-0.1733 ***				-0.3546 ***	
Finance obstacles			0.0952				-0.3112 **
Innovation				-0.1054 ^	-0.0363	-0.0760	-0.2288 ***
Profit up	-0.260 ***				-0.2817 ***		
Profit margin		-2.2792 ***	-0.2384 ***	-2.6269 ***		-2.7278 ***	-2.2365 ***
Leverage up	-0.359 ***	-0.2746 ***	-0.1287 **	-0.3638 ***	-0.4186 ***	-0.3508 ***	-0.1613 *
Real GDP growth	0.042 ***	0.0021	0.0045	0.0928 ***	0.1560 ***	0.0840	0.0838 ***
σ^2	1.218 ***	1.1979 ***	1.0655 ***	1.0888 ***	1.0777 ***	1.0902 ***	0.9751 ***
γ	0.555 ***	0.6206 ***	0.5811 ***	0.6170 ***	0.5090 ***	0.6137 ***	0.5807 ***

N. obs	13,943	12,911	10,172	5,802	5,864	5,687	4,091
Log-likelihood	-17546	-16012	-12354	-6961	-7213	-6805	-4743
Mean PE	0.6320	0.5798	0.5926	0.5859	0.6503	0.5934	0.6155
SD	0.1337	0.1414	0.1274	0.1441	0.1320	0.1426	0.1321
Min	0.0437	0.0444	0.0531	0.0618	0.0443	0.0639	0.0835
Max	0.9303	0.9321	0.9282	0.9306	0.9209	0.9302	0.9286
k	37	37	37	31	32	32	32
AIC	35165	32097	24783	13984	14489	13675	9549
BIC	35444	32373	25050	14190	14703	13888	9752

Source: our elaboration on data from SAFE & BvD AMADEUS.

Significance levels: '***' 0.01, '**' 0.05, '*' 0.10 [^ 0.108].
[a] $\sigma^2 = \sigma_u^2 + \sigma_v^2$; this is composed of the error variance, given by the sum of the variances of the two components.
[b] $\gamma = \frac{\sigma_u^2}{\sigma^2}$; the zero value of this parameter indicates that deviations from the frontier are only due to random error; while values close to one of the range entail that the distance from the border is due to inefficiency. This parameter, in the technique of Jondrow *et al*. (1982) is used to separate the component of inefficiency (JLMS technique).
Moreover, k is the number of estimated parameters; the statistics AIC and BIC are used for models diagnostics.
The econometric results are the simultaneous estimation of the following system of equations:

$$\begin{cases} \log Profit_{it} = \log F_p(y_{it}, w_{it}) + v_{it} - u_{it} \\ u_{it} = F\left(Financial\ constraints_{it}, Innovation_{it}, Performance_{it}, Business\ cycle_{jt}\right) \end{cases}$$

Table 4. Estimation of inefficiency equations for *High-tech* and *Low-tech* sectors

	HIGH-TECH			LOW-TECH		
	(1)	(2)	(3)	(4)	(5)	(6)
Cash flow/Total assets	-5.6028 ***			-5.4167 ***		
Problem of finance		-0.0230			-0.2632 ***	
Finance obstacles			-0.1096			-0.4125 ***
Innovation	-0.2411 ***	-0.2160 ***	-0.1584 **	0.1252 **	0.0784 *	0.0816 *
Profit up	-0.1947 **			-0.1326 **		
Profit margin		-3.5680 ***	-3.2530 ***		-3.0247 ***	-2.6378 ***
Leverage up	-0.3527 ***	-0.2589 ***	-0.2005 **	-0.4743 ***	-0.3424 ***	-0.2224 ***
Real GDP growth	0.1331 ***	0.0549 *	0.0953 ***	0.0789 ***	0.0553 **	0.0559 **
σ^2	0.9815 ***	0.8569 ***	0.7771 ***	1.0687 ***	0.9433 ***	0.8105 ***
γ	0.6612 ***	0.6585 ***	0.6258 ***	0.5509 ***	0.5378 ***	0.4303 ***
N. obs	4,675	4,556	3,348	10,009	9,717	7,128
Log-likelihood	-4992	-4728	-3401	-11985	-11358	-8175
Mean PE	0.6510	0.6272	0.6385	0.6444	0.6233	0.6667
SD	0.1450	0.1421	0.1348	0.1354	0.1271	0.1067
Min	0.0049	0.0052	0.0059	0.0323	0.0449	0.0731
Max	0.9422	0.9500	0.9469	0.9212	0.9875	0.9282
K	32	32	32	32	32	32
AIC	10048	9520	6866	24034	22780	16414
BIC	10254	9726	7062	24265	23010	16634

Source: our elaboration on data from SAFE & BvD AMADEUS.

Significance levels: '***' 0.01, '**' 0.05, '*' 0.10 [^ 17%].
[a] $\sigma^2 = \sigma_u^2 + \sigma_v^2$; this is composed of the error variance, given by the sum of the variances of the two components.
[b] $\gamma = \frac{\sigma_u^2}{\sigma^2}$; the zero value of this parameter indicates that deviations from the frontier are only due to random error; while values close to one of the range entail that the distance from the border is due to inefficiency. This parameter, in the technique of Jondrow *et al*. (1982) is used to separate the component of inefficiency (JLMS technique).
Moreover, k is the number of estimated parameters; the statistics AIC and BIC are used for models diagnostics.
The econometric results are the simultaneous estimation of the following system of equations:

$$\begin{cases} \log Profit_{it} = \log F_p(y_{it}, w_{it}) + v_{it} - u_{it} \\ u_{it} = F\left(Financial\ constraints_{it}, Innovation_{it}, Performance_{it}, Business\ cycle_{jt}\right) \end{cases}$$

For sake of brevity, we report in this Table only the z-variables coefficients.

Table 5. Estimation of inefficiency equations for Micro and Small enterprises

	INDUSTRY			SERVICES		
	(1)	(2)	(3)	(4)	(5)	(6)
Cash flow/Total assets	-6.8553 ***			-3.5471 ***		
Problem of finance		-0.1611 **			-0.1976 *	
Finance obstacles			-0.0927			-0.1850 ^
Innovation	0.0091	-0.0563	-0.0518	-0.0540	-0.1335 *	-0.1352 *
Profit up	-0.2321 ***			-0.1985 **		
Profit margin		-3.1615 ***	-2.8148 ***		-2.2359 ***	-1.6202 ***
Leverage up	-0.3771 ***	-0.1609 **	-0.0894	-0.1834 *	-0.1622 *	-0.0545
Real GDP growth	-0.0186	-0.0120	-0.0148	0.1378 ***	0.0523 *	0.0804 **
σ^2	0.7134 ***	0.5729 ***	0.5513 ***	0.6616 ***	0.7178 ***	0.6114 ***
γ	0.7908 ***	0.7457 ***	0.7606 ***	0.4126 ***	0.5566 ***	0.4754 ***
N. obs	2,876	2,820	2,172	3,626	3,512	2,537
Log-likelihood	-2251	-2200	-1643	-3772	-3582	-2507
Mean PE	0.6764	0.6581	0.6561	0.7195	0.6561	0.6836
SD	0.1599	0.1496	0.1509	0.1213	0.1238	0.1076
Min	0.0243	0.0286	0.0231	0.0620	0.0904	0.1398
Max	0.9644	0.9628	0.9601	0.9320	0.9412	0.9416
k	30	30	30	30	30	30
AIC	4561	4461	3346	7604	7225	5074
BIC	4740	4639	3517	7790	7410	5249

Table 5. Estimation of inefficiency equations for Micro and Small enterprises *(continued)*

	HIGH-TECH			LOW-TECH		
	(1)	(2)	(3)	(4)	(5)	(6)
Cash flow/Total assets	-4.4153 ***			-4.9108 ***		
Problem of finance		0.0209			-0.17821 **	
Finance obstacles			-0.1075			-0.2937 ***
Innovation	-0.2989 ***	-0.2705 ***	-0.1714 *	0.0922 *	0.0318	0.0745 ^^
Profit up	-0.3724 ***			-0.1359 **		
Profit margin		-2.9046 ***	-2.2986 ***		-3.0059 ***	-2.5289 ***
Leverage up	-0.2435 *	-0.1445	0.0009	-0.3019 ***	-0.2162 ***	-0.1165
Real GDP growth	0.0753 *	0.0174	0.0218	0.0366	0.0084	0.0191
σ^2	0.8523 ***	0.7609 ***	0.6435 ***	0.7541 ***	0.7451 ***	0.6348 ***
γ	0.7907 ***	0.7972 ***	0.7655 ***	0.5730 ***	0.6401 ***	0.5526 ***
N. obs	1,863	1,824	1,373	5,683	5,534	4,049
Log-likelihood	-1653	-1602	-1139	-5735	-5490	-3915
Mean PE	0.6409	0.6147	0.6345	0.6802	0.6340	0.6645
SD	0.1681	0.1708	0.1574	0.1358	0.1401	0.1218
Min	0.0289	0.0229	0.0560	0.0391	0.0263	0.1032
Max	0.9342	0.9353	0.9330	0.9577	0.9884	0.9577
k	30	30	30	30	30	30
AIC	3367	3263	2337	11531	11040	7889
BIC	3533	3428	2494	11730	11239	8078

Source: our elaboration on data from SAFE & BvD AMADEUS. Notes; For sake of brevity, we report here only the z-variables coefficients.

Significance levels: '***' 0.01, '**' 0.05, '*' 0.10 [^ 12.2%; ^^ 15.5%].

(a) $\sigma^2 = \sigma_u^2 + \sigma_v^2$; this is composed of the error variance, given by the sum of the variances of the two components.

(b) $\gamma = \frac{\sigma_u^2}{\sigma^2}$; the zero value of this parameter indicates that deviations from the frontier are only due to random error; while values close to one of the range entail that the distance from the border is due to inefficiency. This parameter, in the technique of Jondrow *et al*. (1982) is used to separate the component of inefficiency (JLMS technique). Moreover, k is the number of estimated parameters; the statistics AIC and BIC are used for models diagnostics.

The econometric results are the simultaneous estimation of the following system of equations:

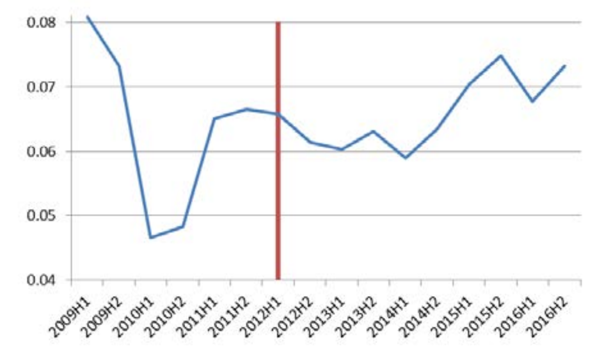
$$\begin{cases} \log Profit_{it} = \log F_p(y_{it}, w_{it}) + v_{it} - u_{it} \\ u_{it} = F\left(Financial\ constraints_{it}, Innovation_{it}, Performance_{it}, Business\ cycle_{jt}\right) \end{cases}$$

For sake of brevity, we report in this Table only the z-variables coefficients.

Figures

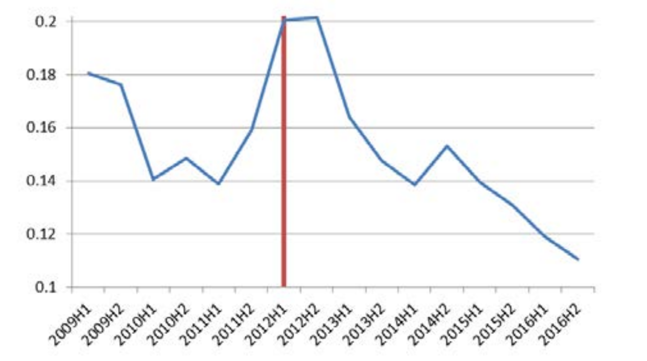
Figure 1. Main regressors over time - Industry

Cash Flow/ Total assets



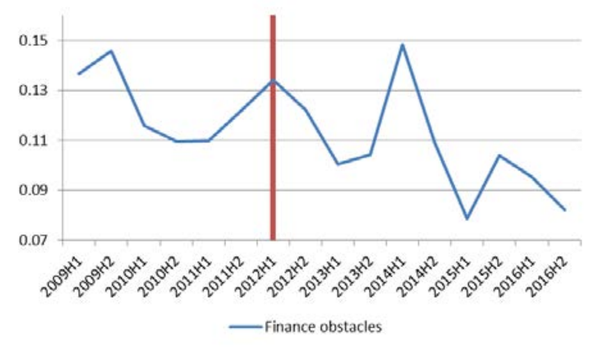
Source: Authors' elaboration on data from SAFE and BvD AMADEUS. Note: Cash Flow is defined as profit (loss) for period plus depreciation. The red vertical line - in correspondence of the 7th wave - indicates the OMT Program.

Problem of finance



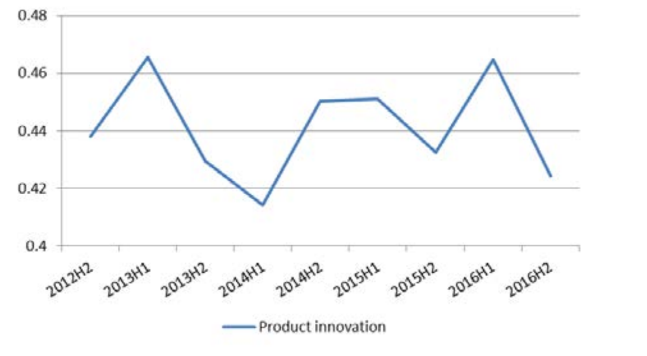
Source: Authors' elaboration on data from SAFE and BvD AMADEUS. Note: *Problem of finance* is defined as is a dummy equal to one if the firm reported that the access to finance represents a relevant problem, and 0 otherwise. The red vertical line - in correspondence of the 7th wave - indicates the OMT Program.

Finance obstacles



Source: Authors' elaboration on data from SAFE and BvD AMADEUS. Note: *Finance obstacles* is a dummy variable equal to 1 if firms report that: 1) their loan applications were rejected; 2) only a limited amount of credit was granted; 3) they themselves rejected the loan offer because the borrowing costs were too high or 4) they did not apply for a loan for fear of rejection (i.e. discouraged borrowers). The red vertical line - in correspondence of the 7th wave - indicates the OMT Program.

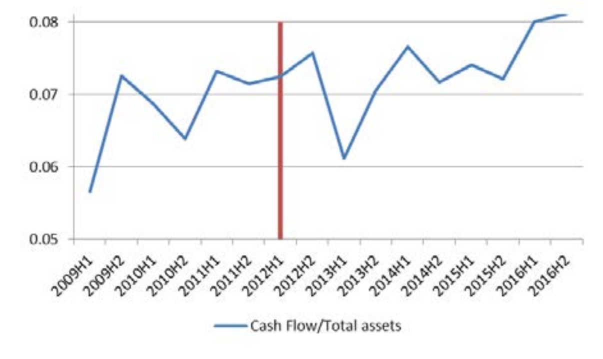
Innovation



Source: Authors' elaboration on data from SAFE and BvD AMADEUS. Note: *Innovation* is a dummy equal to 1 if firms declare in the survey to have undertaken product innovation, and 0 otherwise.

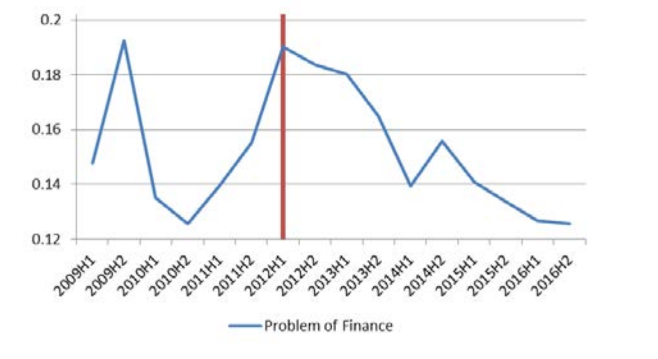
Figure 2. Main regressors over time - Services

Cash Flow/ Total assets



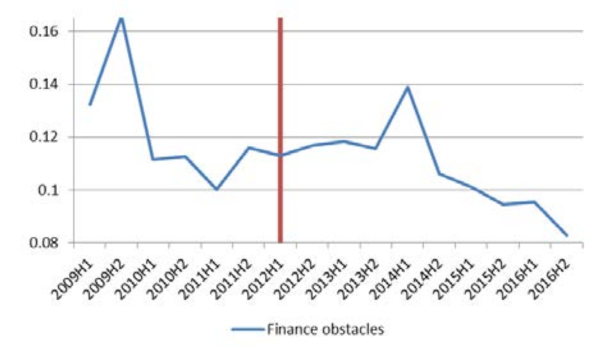
Source: Authors' elaboration on data from SAFE and BvD AMADEUS. Note: Cash Flow is defined as profit (loss) for period plus depreciation. The red vertical line - in correspondence of the 7th wave - indicates the OMT Program.

Problem of finance



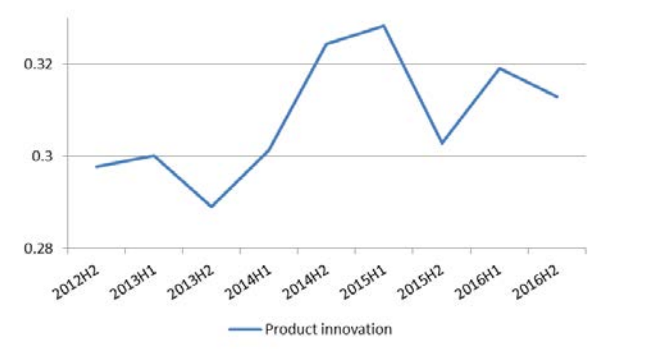
Source: Authors' elaboration on data from SAFE and BvD AMADEUS. Note: *Problem of finance* is defined as is a dummy equal to one if the firm reported that the access to finance represents a relevant problem, and 0 otherwise. The red vertical line - in correspondence of the 7th wave - indicates the OMT Program.

Finance obstacles



Source: Authors' elaboration on data from SAFE and BvD AMADEUS. Note: *Finance obstacles* is a dummy variable equal to 1 if firms report that: 1) their loan applications were rejected; 2) only a limited amount of credit was granted; 3) they themselves rejected the loan offer because the borrowing costs were too high or 4) they did not apply for a loan for fear of rejection (i.e. discouraged borrowers). The red vertical line - in correspondence of the 7th wave - indicates the OMT Program.

Innovation



Source: Authors' elaboration on data from SAFE and BvD AMADEUS. Note: *Innovation* is a dummy equal to 1 if firms declare in the survey to have undertaken product innovation, and 0 otherwise.

Appendix

Table A1. Correlation matrix of the variables used in the inefficiency equation

	Cash flow to total assets♦	Problem of finance♣	Finance obstacles♣	Innovation♣	Financing product innovation♣	Profit up♣	Profit margin♦	Leverage up♣	Real GDP growth
Cash flow to total assets♦	1								
Problem of finance♣	-0.1332*	1							
Finance obstacles♣	-0.1520*	0.3545*	1						
Innovation♣	0.0167*	0.0158*	0.0089*	1					
Financing product innovation♣	0.0019	0.0235*	0.0118*	0.2795*	1				
Profit up♣	0.0594*	-0.0584*	-0.0751*	0.0728*	0.0290*	1			
Profit margin♦	0.4685*	-0.1061*	-0.1156*	0.0095*	0.0048*	0.0336*	1		
Leverage up♣	-0.0865*	0.1348*	0.1262*	0.0216*	0.0238*	-0.0780*	-0.0571*	1	
Real GDP growth	0.0811*	-0.1021*	-0.1019*	-0.001	-0.0205*	0.1649*	0.0477*	-0.0763*	1

Source: our elaboration on data from SAFE & BvD AMADEUS. Legend: ♣ for variables retrieved from SAFE; ♦ for variables retrieved from BvD AMADEUS.

Table A2. Estimation of profit functions and inefficiency equations for HT, MT and LT Industry sectors and for KIS and less-KIS - Specification with *Cash Flow/Total Asset*

	INDUSTRY						SERVICES			
	HT		MT		LT		KIS		less-KIS	
Profit frontier										
Intercept	3.7239	***	2.4292	***	2.2809	***	-0.1191		-0.0880	
Log(Operating revenues)	-0.1674	**	0.0594		0.2376	**	0.7225	***	0.5842	***
Log(wl/wk)	0.8462	***	0.9002	***	0.5648	***	0.7802	***	0.9432	***
Log(Operating revenues)^2	0.1059	***	0.0784	***	0.0227	**	0.0219	**	-0.0058	
Log(wl/wk)2	0.0772	***	0.0706	***	0.0233	***	0.0628	***	-0.0096	
Log(Operating revenues*wl/wk)	-0.0449	***	-0.0516	***	0.0172	***	-0.0523	***	-0.0090	**
Country Effect	Yes		Yes		Yes		Yes		Yes	
Size Effect	Yes		Yes		Yes		Yes		Yes	
Time Effect	Yes		Yes		Yes		Yes		Yes	
Inefficiency equation										
Cash flow/Total assets	-8.0724	***	-8.8443	***	-5.2470	***	-3.5406	***	-4.8488	***
Innovation	-0.3039	***	-0.0603		-0.0320		-0.2864	**	0.3085	***
Profit up	-0.2246	**	-0.1187		-0.0695		-0.2482	^	-0.1376	**
Leverage up	-0.3064	***	-0.4334	***	-0.1494		-0.3849	**	-0.6452	***
Real GDP growth	0.0387		-0.0157		-0.0404		0.1169	*	0.1010	***
σ^2	0.9998	***	0.8655	***	0.8031	***	1.0123	***	1.1311	***
γ	0.7638	***	0.7206	***	0.5744	***	0.6130	***	0.4584	***
N. obs	3,001		2,133		1,931		1,674		5,945	
Log-likelihood	-2880		-1979		-1996		-1887		-7634	
Mean PE	0.6575		0.6846		0.6822		0.6458		0.6477	
SD	0.1580		0.1445		0.1262		0.1358		0.1325	
Min	0.0026		0.0107		0.0415		0.0669		0.0581	

Max	0.9357	0.9404	0.9318	0.9168	0.8987
k	32	32	32	32	32
AIC	5824	4022	4056	3838	15332
BIC	6016	4203	4234	4012	15546

Source: our elaboration on data from SAFE & BvD AMADEUS.

Significance levels: '***' 0.01, '**' 0.05, '*' 0.10 [^ 11%].
[a] $\sigma^2 = \sigma_u^2 + \sigma_v^2$; this is composed of the error variance, given by the sum of the variances of the two components.
[b] $\gamma = \frac{\sigma_u^2}{\sigma^2}$; the zero value of this parameter indicates that deviations from the frontier are only due to random error; while values close to one of the range entail that the distance from the border is due to inefficiency. This parameter, in the technique of Jondrow *et al*. (1982) is used to separate the component of inefficiency (JLMS technique).
Moreover, k is the number of estimated parameters; the statistics AIC and BIC are used for models diagnostics.
The econometric results are the simultaneous estimation of the following system of equations:

$$\begin{cases} \log Profit_{it} = \log F_p(y_{it}, w_{it}) + v_{it} - u_{it} \\ u_{it} = F(Financial\ constraints_{it}, Innovation_{it}, Performance_{it}, Business\ cycle_{jt}) \end{cases}$$

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