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FINANCING INNOVATION FOR SMES ACROSS EUROPE. EVIDENCE FROM MULTILEVEL MODELS

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Financing Innovation for SMEs across Europe.
Evidence from Multilevel Models[1]

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Abstract

This paper aims to evaluate the role played by different sources of finance when analysing firms' attitudes to innovate. The empirical investigation is based on the firm-level data for a large sample of European SMEs across the 2012–2017 period. Different measures of finance and several robustness checks are used to select a well-behaved probit multilevel model. Importantly, results show that the probability to innovate increases when firms use internal finance and grants. The same applies when funds come from family and friend channels, while no conclusive evidence is found for bank loans.

JEL classifications: O31, D21

Keywords: product innovation, financing sources, multilevel model, firm heterogeneity, country effect

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Abstract

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1. Introduction

The uncertainty related to innovation efforts and the presence of asymmetric information characterizing financial contracts render difficult the financing innovation for small and medium-sized enterprises (SMEs) (Acharya & Xu, 2017). It is well known that financial constraints faced by SMEs have several dimensions and appear to be driven by both market distortions in credit allocation (Stiglitz & Weiss, 1981; Nickell & Nicolitsas, 1999) and firms-level factors, such as lack of transparency on their credit records and ability to provide collateral (Cowan et al., 2015; Pigini et al., 2016). Credit obstacles are even more binding during times of financial crisis, leading to credit rationing or suboptimal financing activities to SMEs (Agénor & da Silva, 2017; Carbo-Valverde et al., 2015; Popov & Udell, 2012; Popov & Van Horen, 2014).

A significant strand of literature has documented that firm innovative activities face more binding financial constraints than do fixed capital investments (Mateut, 2018). This is because innovation is characterized by a high degree of uncertainty, due to its lack of collateral value (Hall, 1992), unknown long-term returns (Pindyck, 1993), its irreversibility (Dixit & Pindyck, 1994) and unpredictable market acceptance (Tyagi, 2006). A further aspect to consider is the presence of asymmetric information on the value of innovation projects (Griliches, 1995), which might induce adverse selection and moral hazard between borrowers and lenders (Rajan & Zingales, 2001). In light of these uncertainties and asymmetries, external lenders – typically banks – are usually not prone to finance investments in innovation, since they prefer to fund low-risk projects, or they require collateral to secure debt (Guariglia & Liu, 2014). It is also argued that innovative firms, often leveraged and with a low cash flow, might face a higher likelihood to encounter financial distress (Opler & Titman, 1994). Therefore, innovative firms tend not to use the bank channel as a favourite source of financing (Bah & Dumontier, 2001; Chiao, 2002; Hall, 1994; Hall, 2002; Brown et al., 2012).[2]

Coupled with this matter, some literature (Himmelberg & Petersen, 1994; Mulkay et al., 2001) has investigated the role played by internal finance in firm R&D activity. Given the risky nature of innovation and the scarcity of external financing, firms often prefer to finance their innovation projects with internal funds, which have the advantages of lower cost, fewer constraints and lower risk (Bougheas et al., 2003; Chiao, 2002). It has also been shown (Fazzari et al., 1988; Hall & Lerner, 2010; Hottenrott & Peters, 2012) that internal and external funds might be complementary, rather than substitute for each other, depending on factors such as the stage of the innovation project (García-Quevedo et al., 2018). Often internal resources are insufficient for financing firms' innovation activities, so firms need to resort to debt financing (Kerr & Nanda, 2015; García-Quevedo et al., 2018).

Additionally, a bulk of literature deals with the effects that a number of country observables have on innovation. Within this field of research, some studies have examined, for instance, the effect of policy and policy uncertainty on technological innovation (Bhattacharya et al., 2017); others have considered the effects of laws (Acharya & Subramanian, 2009; Acharya et al., 2013) and banking competition (Cornaggia et al., 2015) on the innovation efforts. As for the effects of the country's financial development, i.e., stock market and credit market development for R&D investment, Brown et al. (2013) document that, in well-developed stock markets, access to equity financing exerts a positive impact on innovation. Importantly, Hsu et al. (2014) report that stock markets have a positive impact on innovation, while the contrary holds for credit markets.

This paper's motivation builds on the abovementioned literature. Although the previous studies have widely analysed the effect of financial constraints on innovation efforts, to the best of our knowledge, little attention has been paid to assessing the impact of the different types of

[2] Differing from this evidence, Ayyagari et al. (2011) document a positive link between bank financing and firm innovation efforts for emerging countries.

financial sources on the innovation activities undertaken by SMEs. This aspect is relevant because firms need to know which type of financial source is most appropriate for developing their innovation project. Finally, given the difficulties for SMEs to finance innovation, the choice between internal and external financing sources appears to be not neutral for the firms' innovation choices (Fazzari et al., 1988). Another distinguishing feature of the work is that we control for the country-specific unobservable effects within a single framework.

Based on these considerations, the analysis aims at investigating the effect of different financing channels, available for SMEs, on the firms' probability to embark on product innovation efforts. Specifically, we test whether internal resources are more or less relevant than external formal financing (bank credit), than public grants and subsidies and than informal financing channels (family, friends). In addition, we assess how much of the heterogeneity in firms' probability to innovate can be attributed to individual characteristics and how much of it reflects country features across Europe.

To address these issues, we follow the multilevel modelling approach, which allows us to exploit the hierarchical structure of data. Indeed, SMEs are embedded in countries: they are at the lowest level of the hierarchy, and the countries are at the highest (Goldstein, 2003; Luke, 2004). Compared to single-equation models, multilevel models (MLMs) are more attractive as they address some statistical issues (*cf.* Section 3.1) and also because they allow an understanding of how the micro-, mid- and macro-spheres of economic systems evolve and interact (Baldwin & Okubo, 2005; Beugelsdijk, 2007). Given the bivariate nature of the dependent variable (the firm undertakes innovation or not), we use a probit MLM, where the country effect is modelled to capture the source of randomness in the intercepts (Goldstein, 2003; Luke, 2004).

The analysis is based on a large sample of European SMEs observed during the period 2012–2017. Firm-level data are retrieved from the Survey on the Access to Finance of Enterprises (SAFE) run by the European Central Bank (ECB). SAFE is the only harmonized and homogeneous dataset providing relevant information to address our research questions. Specifically, SAFE offers the appropriate information for testing the complex links among the decision to innovate, the different types of financing sources and the firm's financial constraints, that we aim to investigate. Although SAFE does not provide balance sheet data, it presents a number of relevant advantages. First, it allows us to trace over time a company's decision to develop and launch new products and services on the markets, and to discern different types of financing sources used by firms. Moreover, SAFE offers qualitative information on firms' experience in accessing credit and on the financial problems that SMEs may encounter. Finally, data are available for a large sample of European SMEs, allowing us to take cross-country heterogeneity into account.

The study's contributions are twofold. First, it focuses on the interplay between firm access to finance and the probability to undertake innovation. We test the effect of different financing sources (i.e., bank loans, internal funds, grant or subsidies, loans from family or friends and equity) on the probability to introduce a product innovation, net of the impact exerted by geographical contexts. Second, we address how unobservable cross-country heterogeneity shapes the probability at firm level to undertake innovation.

Having found high variability across firms and European countries, we confirm that firm-specific characteristics greatly affect the individual propensity to innovate. The country effect explains about 4% of the variance of the firms' innovative behaviour. Additionally, results show that innovation is strongly influenced by the different sources of financing and, in particular, by internal finance and grants. Results are robust to several model specifications.

The remainder of the paper is structured as follows. Section 2 briefly presents the economic theory to which the paper refers. Sections 3 and 4 describe the analytical framework and the empirical setting, respectively. Section 5 presents and discusses the results. Section 6 offers some concluding remarks.

2. The underlying theory

The link between capital structure and firm performance has been widely investigated in literature. A large spectrum of papers originating in the Modigliani-Miller theory (Modigliani & Miller, 1958) has focused on the firm assets composition and firm value by looking at the different sources of firm financing, particularly at the equity-debt mix (Kraus & Litzenberger, 1973; Myers, 1984; Fischer et al., 1989; Myers & Majluf, 1984; Ross, 1977; Baker & Wurgler, 2002). Economists agree that when the financial markets are imperfect, the internal and external sources of finance are not interchangeable. However, if the internal finance is insufficient, firms tend to reduce their optimum investment (Myers & Majluf, 1984). A firm is, therefore, subject to financial constraints when it is obliged to renounce investment projects which it is not in a position to finance, profitable though they may be.

There is considerable evidence that firms encounter financial constraints when they invest in physical capital (Fazzari et al., 1988; Bond et al., 2003). Far less research, however, has been dedicated to the problem of investments in R&D (Harhoff, 1998; Bond et al., 1999), even though a number of elements suggest that financial obstacles are far more likely to exist when investments are in R&D rather than in physical capital (Mateut, 2018). This is because the link between R&D investment and the firms' financing sources is more complex than for ordinary fixed investment. First and foremost, it is much more difficult to assess both the proposed investment projects and the creditworthiness of the firm itself (Bond et al., 1999; Hall, 1999). Second, the fact that the investments are in projects which will not prove profitable in the short – or medium – term, and which are also, by their very nature, of uncertain outcome, places R&D investments at a disadvantage in the search for credit (Pindyck, 1993; Dixit & Pindyck, 1994; Tyagi, 2006). Furthermore, as regards innovation, the strategic behavior of firms increases asymmetric information, and this factor illustrates the complexity of the risk assessment when incurring debt to finance R&D. Finally, these difficulties extend to the use of risk capital: given asymmetric information and uncertain outcome, capital markets tend to undervalue the new shares, thereby penalizing the existing shareholders (Fazzari et al., 1988; Griliches, 1995; Rajan & Zingales, 2001).

All these factors yield two results. On the one hand, firms face higher costs of external than internal capital for R&D (David et al., 2000; Hall, 2002; Cosh et al., 2009; Hall & Lerner, 2010; Mina et al., 2013). On the other hand, these frictions produce underinvestment in R&D activities (Meuleman & De Maeseneire, 2012), which might be below the social optimal level (Nelson, 1959; Arrow, 1962).

The underinvestment in R&D is even more binding for SMEs, which are the ones contained in the SAFE dataset. Given the risky nature of innovation and the scarcity of external financing, SMEs often prefer to finance their innovation activities using internal funds, which have the advantages of lower cost, fewer constraints and lower risk (Bougheas et al., 2003; Chiao, 2002). Finally, some literature underlines that internal and external funds could be complementary, rather than substitute for each other (Fazzari et al., 1988; Hall & Lerner, 2010; Hottenrott & Peters, 2012) depending on factors such as the stage of the innovation project (Kerr & Nanda, 2015; García-Quevedo et al., 2018).

The empirical setting of the analysis is rooted in the theory that we briefly summarized and is specified as follows.

3. The analytical framework

3.1 The multilevel model in a nutshell

Understanding whether and how market and environmental conditions affect SMEs' performance is a typical example of hierarchy, in the sense that the units (firms) refer to different levels of aggregation (local markets, country) (Goldstein, 2003). In this respect, MLMs fit this nested structure of data well and yield more reliable estimates than a single-equation model. Indeed, variables at any level of the hierarchy are not simply add-ons to the same single-level equation, but are linked together in ways that make the simultaneous existence of distinct level-one and level-two equations explicit. This allows the evaluation of whether, and to what extent, contextual factors matter in determining firms' performance. On the one hand, the role of contextual factors is detected by testing hypotheses operating at different levels; on the other hand, MLMs decompose heterogeneity in the output variable, providing a highly informative outcome on "how much" contextual and individual factors contribute to the heterogeneity in firms' performance (Bickel, 2007; Heck & Thomas, 2000; Rabe-Hesketh & Skondal, 2008; Richter, 2006). Furthermore, MLMs address the issue of error correlation across SMEs, thereby controlling for spatial dependence, and they correct the measurement of standard errors (Hox, 2002).[3] Finally, MLMs address the ecological and atomistic fallacies, because they take firm and country levels into account simultaneously (Maas & Hox, 2004; Snijders & Berkhof, 2008).[4]

All these methodological advantages also render the MLMs original from an economic perspective, because they address how the "micro, middle and macro" (Schumpeter, 1934) spheres of economic systems evolve and interact in any process of growth.

The originality of the approach in the empirics of firm performance lies in the fact that the hierarchical interactions between agents – individual firms – and external growth-factors are not studied in an exhaustive way in the literature (Raspe & van Oort, 2011; Srholec, 2010).[5] In more

[3] In more detail, the single-equation models suffer from some estimation problems. First, as a result of locally specific factors, SMEs operating in a market are likely to be more similar than SMEs located in different areas, implying that residuals are not independent. This issue is addressed by the multilevel approach, which, controlling for territorial effects, ensures more efficient estimates than those of the single-equation model (see, i.e., Rabe-Hasketh & Skondal, 2008). Furthermore, single-level regressions yield an inflated significance of level-two coefficients because the diagnostics refers to the number of level-one observations instead of the number of higher-level units. Conversely, in MLMs, the inference is made by distinguishing between sample sizes at the different levels of data aggregation. One consequence of failing to recognize hierarchical structures is that standard errors of OLS coefficients will be underestimated, thus increasing the risk of type I errors (Hox, 2002; Snijders & Berkhof, 2008). There is another potential bonus in the unbiasedness of results. Indeed, in many economic problems, the groups differ in size, and in such unbalanced set-ups, the multilevel approach assigns greater weight to large groups than small ones.

[4] The ecological fallacy occurs when a result obtained at an aggregate level is not automatically confirmed after the analysis is replicated on an individual basis. Hence, micro-founded analysis is preferable, since it controls for any potential aggregation bias. On the contrary, working with micro-data leads to the opposite issue, related to the absence of any link between individual-level and group-level relationships (atomistic fallacy) (Raspe & van Oort, 2011).

[5] An example from growth literature models helps with the understanding of this issue. The endogenous growth theory pays much attention to proving the existence of increasing returns due to R&D spillovers between firms and other organizations (Romer, 1990; Aghion et al., 2004). However, they are macro models and focus on aggregate patterns, although they have micro-foundations. Again, the evolutionist scholars explain that the environment plays a dominant role in influencing firms' attitudes to innovation, even though the micro-macro interactions are one-way, flowing from the individual to the aggregate level (Dosi & Nelson, 2010). This implies that the "overall" patterns are just those from aggregations, while any other important environmental factor is left out of the analysis (Castellacci, 2007). The link

detail, no study uses the MLM approach to explain the relationship between finance and firm attitude to innovate, whereas some attention has been paid by MLM scholars to studying the firm productivity issue.[6]

3.2 The multilevel model for binary dependent variables

The analysis focuses on a sample of European SMEs which are observed over the 2012–2017 period. SMEs are embedded in national markets and the hierarchy is composed of two levels. Multiple measurements of individual efficiency at different time points represent level 1 of the hierarchy. Punctual-time SMEs' observations are nested in geographical markets (country), representing level 2 of the structure. This is standard in MLM literature (Steele 2008).

Referring to the notation proposed by Raudenbush and Bryk (2002), we use the following model:

$$Product\ Innovation_{itj} \sim Bernoulli\left(\varphi_{itj}\right) \qquad [1]$$

$$Probit\left(\varphi_{itj}\right) = \eta_{itj} \qquad [2]$$

$$\eta_{itj} = \beta_{0j} + \sum \Omega_k x_{kit} + e_{itj} \qquad [3]$$

where *i* identifies the firm, *j* the countries and *t* the time. In addition, equation [1] is the level-1 sampling model; equation [2] is the link function; and equation [3] is the structural model. In eq. [3], x_{kit} are the predictor variables and Ω_k includes all the parameters to be estimated. The level-2 model for the random intercept β_{0j} is written as:

$$\beta_{0j} = \gamma_{00} + u_{0j} \qquad [4]$$

where γ_{00} is weighted average of the intercept across all countries and u_{0j} is the residual or random intercept capturing the variability in the intercept across countries. It is defined at the group level

between this literature and the multilevel approach is in the basic idea that each firm is embedded in a specific economic system. The implication of this is that firm performance is understood as a systemic-shared issue, which cannot be addressed without modeling the interactions from micro to macro level, and vice versa, as multilevel does (Baldwin & Okubo 2005; Beugelsdijk, 2007). Hence, multilevel represents an important contribution in the empirical studies of firm performance aimed at understanding the essential links between micro and macro patterns (Aiello et al., 2014; Raspe & van Oort, 2011; Srholec, 2010; 2015).

[6] For instance, Raspe and van Oort (2011) link firm productivity to the knowledge-intensive spatial contexts in the Netherlands and find that a large part of what is considered the effect of spatial externalities should actually be the effect of firm-specific characteristics. Fazio and Piacentino (2010) investigate the spatial variability of firms' labour productivity, while Aiello et al. (2014) analyse how firms' characteristics and regional factors affect TFP heterogeneity. Mahlberg et al. (2013), with reference to Austria, explore the link between age and labour productivity. A related topic is innovation, which, in the framework of multilevel analyses, is investigated by Srholec (2015). He shows how national conditions affect the propensity of firms to cooperate on innovation at home or abroad. Finally, Aiello and Ricotta (2016) show that firm-specific determinants are the most important source of TFP heterogeneity across Europe. However, they also indicate that location matters, in the sense that the context where firms operate plays a prominent role in determining individual TFP.

with zero mean and assumed to be independent of e_{itj}. Combining micro (eq. 3) and macro (eq. 4) models yields a two-level mixed equation:

$$\eta_{itj} = \gamma_{00} + \sum \Omega_k x_{kit} + (u_{0j} + e_{itj}) \qquad [5]$$

The deterministic part of the model – $\gamma_{00} + \sum \Omega_k x_{kit}$ – contains all the fixed coefficients, while the stochastic component is in brackets. The error term captures the residual variance, in the same way as standard probit regression does, and the group-to-group variability of the random intercepts. It is clear that the error term displayed in eq. [5] is not independently distributed. Indeed, as data are nested at different levels of analysis, firms belonging to the same group tend to have correlated residuals, thus violating the assumption of independence.

Eq. [5] also allows for the identification of the errors resulting from differences across firms or clusters. To this end, it is necessary to use an "empty" model, i.e., a model without any explanatory variables:

$$\eta_{itj} = \gamma_{00} + u_{0j} + e_{itj} \qquad [6]$$

From eq. [6] is possible to decompose the variance of η_{itj} into two independent components, i.e., the variance of e_{ij} (σ_e^2), the so-called within-group variance, and the variance of u_{0j} (σ_{u0}^2), also known as between-group variance. A useful way to interpret the relative magnitude of the variance components is to compute the intra-class correlation (*ICC*), which measures the proportion of total variance "explained" by the grouping structure, that is, the intra-class correlation for our second level of analysis, i.e., country. Specifically, $ICC\ country = \frac{\sigma_{\mu 0}^2}{\sigma_{\mu 0}^2 + \sigma_e^2}$, where $\sigma_{\mu 0}^2$ is the so-called between-group variance and σ_e^2 is the so-called within-group variance. This index measures how much of the variability of the probability to innovate is explained by the country dimension.

4. The empirical setting

4.1 The econometric specification

The econometric specification of eq. (5) is the following:

$$P\left(Product\ Innovation_{itj}\right) = \gamma_{00} + F\left(Firm\ financing_{l(i,t-2)},\ Ownership_{m(i,t)},\ Z_{r(i,t)}\ ,\ W_{s(j,t)}\right) + u_{0j} + e_{itj} \qquad [7]$$

where the dependent variable is a dummy equal to 1 if the firm declares to have launched new products or services at time *t*, and 0 otherwise.[7] The main explanatory variables are in the vector *Firm financing*$_{(i,t\text{-}2)}$, which is meant to capture firm experience in the use of different financing sources. It includes one variable capturing the use of each channel of finance. These variables are the following: *Use Internal Funds*$_{(i,t\text{-}2)}$, *Use Bank Loans*$_{(i,t\text{-}2)}$[8], *Use Grants or Subsidies*$_{(i,t\text{-}2)}$, *Use Family or Friends Loans*$_{(i,t\text{-}2)}$ and *Use Equity*$_{(i,t\text{-}2)}$. They are dummy variables equal to 1 if the related financing source is used by the reporting firm, and 0 otherwise. To limit the causal relationship and potential endogeneity bias, we use two-periods lagged explanatory variables.

The vector *Ownership*$_{m(i,t)}$ includes a set of dummy variables to control for ownership types (with m=1,…,4): Family, One owner, Public company and Venture Capitalist or Business Angels owners (VCBA). A residual category of ownership types (Other ownership) represents the control group. Furthermore, $Z_{r(i,t)}$ identifies a set of standard firm controls. They are *Size*, which is gauged by referring to firm turnover (Medium-sized and Large), *Age* (Young, Medium-aged, Old) and *Sector* (Industry, Construction and Trade).[9] Finally, W_{sjt} includes the wave dummies in order to control for the time effect, with s=1..9.

4.2 Data and descriptive statistics

The empirical analysis is based on data from SAFE, which is jointly run by the ECB and the European Commission (EC) every six months (a *wave*) since 2009. It is a harmonized and homogeneous dataset providing information at the micro level about SMEs' financial needs, financial sources, as well as other firm-level characteristics and the types of innovation undertaken by SMEs. Each wave of the SAFE is addressed to a randomly selected sample of non-financial

[7] Differing from the other variables in the sample, the information on *Product Innovation* (Q1 in the Survey) refers to the previous 12 months and, therefore, is provided by SAFE every second wave. 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] SAFE also provides information on the use of bank credit lines. In order to have a broader measure of the use of bank credit, we construct the dummy *Use Bank Credit*$_{(i,t\text{-}2)}$, 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. While the baseline regressions always include the variable *Use Bank Loans*$_{(i,t\text{-}2)}$ (it is more suited for financing long-term investment), we alternatively employ the dummy *Use Bank Credit*$_{(i,t\text{-}2)}$ as a robustness check.

[9] As regards size, we use three classes of turnover: Small, Medium-sized and Large. The two dummies, Medium-sized and Large, are equal to 1 if the firm registers a turnover between 2 and 10 million (euros), and between 10 and 50 million (euros), respectively, and 0 otherwise. As for the age of the firms, Young, Medium-aged and Old are dummies equal to 1 if the firm is less than 2 years, between 2 and 5 years, and between 5 and 10 years old, respectively, and 0 otherwise. As for the sector composition, firms in the sample operate in the four largest economic sectors at 1-digit level of the NACE classification, i.e., Industry (which includes manufacturing, mining and electricity, gas and water supply), Construction, Trade and Services. The controlling groups for Size, Age and Sector are Small, Very old and Services, respectively.

SMEs included in the Dun & Bradstreet business register; exceptions are made for firms in agriculture, public administration and financial services that are intentionally omitted. Country, sector and size representativeness are ensured through the use of specific weights. SAFE also provides information on firms' innovation (Product innovation). We thus restrict our analysis to the period during which the information needed for the analysis is part of the surveys; namely, we consider the data from the 8th to the 17th wave. Using the same criterion, we select those countries for which the related firms' data are available across the waves.[10] The sample covers the period from 2012 to 2017.

[Insert Table 1]

Summary statistics of the variables used in the econometric analysis are displayed in Table 1. Throughout the period under investigation, the sample comprises 24,663 firm-level observations. After averaging data by country and year, it emerges that the proportion of innovative firms, namely those that have introduced a product innovation, is 34%. The standard deviation (0.47) signals that there is certain variability in the distribution of product innovation. Figure 1 confirms the well-known national disparities in innovative activity across Europe: the average proportion of SAFE product innovators varies not only country-by-country but also over time. The peaks in the distribution are 55% (Finland in 2017) and 50% (Czech Republic in 2014). Bearing in mind the specific objective of the paper, it is also useful to detect the cross-country variability in the share of firms using the different sources of finance. It emerges that banking and internal funds are more relevant than the other channels: 27% of firms declared the use of funds loans from banks, 53% of the sample use either bank loans or credit lines or both these finance sources and 24% take recourse to internal funds. At the opposite side, 3% of firms use equity. Interestingly, 12% of firms use grants or subsidies.

[Insert Figure 1]

[10] The countries included in the sample are Austria, Belgium, Bulgaria, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, the Netherlands, Poland, Portugal, Romania, Slovakia, Spain, Sweden and the UK. We have excluded countries with fewer than 300 firm-year observations during the period under scrutiny (Albania, Croatia, Cyprus, Estonia, Iceland, Latvia, Lithuania, Luxembourg, Macedonia, Malta, Montenegro, Russia, Slovenia, Turkey). Appendix Table A1 reports firms' distribution by country. Many firms are in France, Germany, Italy and Spain (about 3,000 firms in each country), followed by Austria, Belgium, Greece, Ireland, the Netherlands, Poland, Portugal and the UK (more than 1,000 firms), Finland (980), Slovakia (508) and Bulgaria, Czech Republic, Denmark, Hungary, Romania and Sweden (fewer than 500 firms in each country).

To complement this information, Figures 2–4 provide further details regarding spatial and time variability of the main financing sources (internal fund, bank loans, grant or subsidies, family and friends loans, equity) used by the firms in the SAFE sample. For each finance channel, data display the strong firm heterogeneity across time and country, which underpins the motivation for this research.

[Insert Figures 2, 3, 4]

Regarding ownership, data in Table 1 reveal that about 50% of the sample are Family firms and 29% have a Single owner, while the proportion of VCBA-owned firms is small (0.6%). This comes as no surprise in light of the specific countries and the type of firms we are considering. In our sample, 44% of firms are classified as small companies, 46% are medium-sized and only 9% are large. It also emerges that most of the companies are classified as very old (84%), and only a tiny share of the sample is represented by young firms (0.8%). Finally, firms in Service are 34% of the sample, Industry and Trade each account for about a quarter of the sample and Construction is the least numerous sector (10%).

What the data highlight is a considerable heterogeneity both in individual attitude to innovate and in firm-specific characteristics, especially where the channels of financing business activity are concerned. The following section presents the results obtained from applying the probit multilevel model to quantify and discuss to what extent firm heterogeneity in the attitude to innovate is due to firm-specific factors, and how much can be explained by the localisation in different European countries.

5. Empirical Results

5.1 Some diagnostics and the explained firm heterogeneity

This section refers to the estimations obtained when considering the empty multilevel probit model, which allows us to evaluate how much of the variation in outcomes might be attributable only to unobserved factors operating at each level of the hierarchy. Here, it is noteworthy that SAFE classifies firms into four sectors and this prevents us from considering sector as a level of the model. Indeed, the multilevel approach ensures reliable estimations only when the group size is at least 20.[11] As discussed in Sections 3 and 4 (eq. [1]–[7]), we restrict the data hierarchy to two levels

[11] In the multilevel approach, a key issue to be addressed concerns the sample size at any level of analysis. Indeed, the requirements of precise measurement of between-group variance impose a “sufficient” number of clusters. Although

(firms and countries) and model the sector membership by using dummies. In brief, throughout the paper the preferred model specification is that which treats countries as sources of randomness in the intercepts, while sectors are modelled as fixed effects.

Results are displayed in Table 2, where the different specifications vary according to the progressive inclusion of the covariates. The first column refers to the MLM probit empty model (eq. [6]). Column 2 adds the set of variables named *Firm financing* (eq. [7]), gathering all the different sources of internal and external financing used by SMEs. Column 3 includes the control for ownership. Finally, column 4 refers to the model controlling for the age, size, sector and time fixed effects.

[Insert Table 2]

The first finding to be discussed is the likelihood-ratio test, which compares the empty models with the standard probit regression: under H_0 we have that $\sigma_{u0}^2 = 0$, hence there is no random intercept in the model. If the null hypothesis is true, standard probit regression can be used instead of a variance-components model. The test, which is highly significant, supports the use of multilevel methodology and indicates that the intercept should be considered as a group-by-group variant coefficient. Importantly, the evidence in favour of the multilevel approach holds for each model specification considered throughout the paper (see Tables 2 and 3). Additionally, some remarks regarding the model come from Figure 5, which adds to Figure 1 the estimated probability to innovate, averaging the firm values by country and by year. After observing country-by-country that the estimated probability is barely equal to the observed proportion of product innovators, one can argue that the common model specification (eq. [7]) for the 20 countries on which the analysis is based fits the data well.

[Insert Figure 5]

there are some, albeit very different from each other, rules of thumb, a clear indication does not exist in this respect (Richter 2006). Some authors suggest that 20 is a sufficient number of groups (Heck & Thomas, 2000; Rabe-Hasketh & Skondal, 2008), others 30 (Hox, 2002) or 50 (Mass & Hox, 2004). In addition, it is worth noting that in random-effects models the clusters must be sized with at least two observations. The alternative is a fixed-effects approach in which the number of groups is not important, although their dimension then becomes crucial as the estimated group effect is unreliable for small-sized groups. These numbers condition our empirical setting: the preferred specification is a two-level random-intercept model where firms and countries are treated as source of randomness and sectors are modelled with dummy variables.

As can be seen from the estimations of the empty model (column 1 of Table 2), the ICC indicates that country-specific factors capture 3.29% of the total variance of product innovation, while the remaining variance (96.71%) is explained by firms. When augmenting the model with the variables gauging the firm specific characteristics (models 2-4 in Table 2), the unexplained variation in the probability to innovate which lies at the national level is always no more than 3.5%, while the internal firm characteristics capture more than 96% of firms' variance. These results hold in the sensitivity analysis (see Table 3).

The key finding from Table 2 regards the role of firm-specific factors as the dominant source of heterogeneity when analysing the propensity to innovate of the SAFE sample. Whatever the model specification, the share of variability due to unobserved firm-specific factors always exceeds 96%.

5.2 The probability to innovate and the roles of different channels of finance

The econometric results obtained when assessing the relationship between finance and the probability to innovate are noteworthy. Regressions show that the use of bank loans does not exert any influence on the firm's probability to introduce a product innovation. Rather, it appears that the firms using internal resources face a higher probability to develop or launch new products and services.

This evidence is documented by the fact that the coefficients on the use of bank loans never turn out to be significant, while the ones on the use of internal financing always exhibit a positive and highly significant sign.[12] This evidence holds moving from the regression, which comprises the channels of finance only (model 2 of Table 2), to the augmented regression with firm-type by ownership and a set of fixed-effect controls (time, size, age and sector) (model 4 in Table 2). Importantly, there is no qualitative difference of the relationship between bank or family finance and product innovation when a sensitivity analysis is performed (*cf.* Table 3). Hence, the estimates seem to provide solid evidence supporting the hypothesis that there is a credit rationing phenomenon in capital markets for SMEs. Indeed, given the presence of asymmetric information in financial markets, borrowing external funds for firms turns to be more expensive than using internal

[12] To corroborate our result, we have re-estimated our model using the broader variable for bank credit, *Use Bank Credit*, capturing the use of both bank loans and bank credit lines. Estimates confirm our previous evidence, as the dummy *Use Bank Credit*$_{(i,t-2)}$ never turns out to be significant. Results – not reported here for the sake of brevity – are available upon request.

finance (Nickell & Nicolitsas, 1999). In brief, the use of available internal finance, i.e., use of cash flow, signals that firms are financially constrained (Fazzari et al., 1988; Guariglia & Liu, 2014; Sasidharan et al., 2015).

This view is also corroborated by the positive and significant signs of the variable *Use of grant*. In the presence of market failures, the use of public support for SMEs may be crucial for backing their investment in intangibles, given the uncertainty related to innovation efforts. Differently phrased, such evidence supports the view that government subsidies are a useful tool to spur innovation as they lessen credit constraints that SMEs may face in their access to finance (Meuleman & Maeseneire, 2012). Additionally, estimations document the importance of family and friends as informal channels to finance innovation. This result can be motivated by the fact that the sample is mainly constituted by micro and small firms, which often face difficulties in accessing formal external financing due to lack of transparency on their credit records and ability to provide collateral (Cowan et al., 2015; Pigini et al., 2016).

The magnitude of the marginal effects displayed in Table 2 allows the ranking of the impact of the different sources of financing and the several types of ownership on the probability for firms to embark in product innovation. Specifically, the use of internal funds increases the likelihood to undertake product innovation by a value that ranges from 3.01% (model 4) % to 3.69% (model 2). The probability to innovate increases by 3.93% (model 3) or 4.31% (model 2) when firms recur to loans from family and friends, while it increases by a value ranging from 5.29% (model 4) to 5.84% (model 2) when using equity. When firms resort to subsidies or grants, the probability to introduce a product innovation rises to 8.36% (model 2)

As for the other firm-varying controls, ownership plays an important role in the probability of starting innovation activities. Interestingly, venture capital and business angel (VCBA) ownership exerts a significant effect on the probability to embark on product innovation. We find the same evidence for public companies, while the coefficients of family businesses and single-owned firms are significant and display a negative sign. To sum up, the signs of the ownership coefficients support the notion that less traditional and more dynamic forms of ownership stimulate firms towards innovation efforts, which are crucial to obtain a strategic advantage over competitors (Paul et al., 2017).

The marginal effects of the ownership controls (*cf.* Table 2) show that VCBA ownership increases the probability of starting innovation activities by 10.8 % (model 4) or 12.85% (model 3). Another finding is that being a public company increases the likelihood to embark on product innovation by more than 7%. Finally, single-owned and family businesses firms face a lower probability to innovate (-3.88% and -3.12 in model 3 and -1.8% and -1.85 in model 4, respectively). These figures underpin the view that the more groundbreaking forms of ownership favor firms' inclinations towards innovation efforts.

5.3 A sensitivity analysis

In order to provide additional support to the main results, we re-run the probability model (eq. 7) by augmenting the regressions with a wide range of additional firm level controls. They refer to some indicators of firm performance and proxies for other constraints/problems that distress SMEs.[13]

In the model 1 of Table 3, we rely on a set of controls meant to take into account the potential relationship between innovation and past firm performance. They are as follows. *Profit up*$_{(i,t-2)}$ is a dummy equal to 1 if the firm declares that its profits increased in the last six months, and 0 otherwise. *Cost of labour up*$_{(i,t-2)}$, *Other cost up*$_{(i,t-2)}$ and *Interest expenses up*$_{(i,t-2)}$ are dummies equal to 1 if the firm declares that the cost of labour, other costs or interest expenses have increased, respectively, and 0 otherwise. *Leverage up*$_{(i,t-2)}$ is equal to 1 if the firm declares that the ratio between debts and total assets has increased, and 0 otherwise. *Credit History up*$_{(i,t-2)}$ is a dummy equal to 1 if the firm declares that its creditworthiness increased in the last six months, and 0 otherwise.

It is also of some interest to verify the robustness of the main results when including some controls related to market conditions. In this respect, we consider a section of the SAFE survey regarding the problems faced by firms in the last six months. The indicators are the following. *Problem of finance*$_{(i,t-2)}$ is a dummy equal to 1 if the firm reports that the access to finance was perceived as an obstacle in the last six months, and 0 otherwise. *Problem of cost of production*$_{(i,t-2)}$ is a dummy equal to 1 if the company states that the cost of production turned into a major obstacle, and 0 otherwise. *Problem of availability of skilled staff*$_{(i,t-2)}$ is a dummy equal to 1 if the firms face some difficulties in finding high-skill employees or experienced managers, and 0 otherwise. *Problem of finding customers*$_{(i,t-2)}$ is a dummy equal to 1 if the firm states that finding customers was difficult in the last six months, and 0 otherwise. *Problem of regulation*$_{(i,t-2)}$ is a dummy equal to 1 if the firm declares that regulations (European and national laws or industrial regulations) were perceived as an obstacle in the last six months, and 0 otherwise. Finally, *Problem of competition*$_{(i,t-2)}$ is a dummy equal to 1 if the firm reports that the "problem of competition" –due to either external

[13] The descriptive statistics of these additional controls are reported in the Appendix (Table A2).

market conditions or an internal loss in firm efficiency – has become more relevant, and zero otherwise. As in the baseline model (*cf*. Table 2), to limit the causal relationship and potential endogeneity bias, we use two-periods lagged explanatory variables.

In model 2 of Table 3, we use two additional variables to control for firm growth: *Employees up*$_{(i,t-2)}$ is a dummy equal to 1 if the firm declares that the number of its employees has increased, and 0 otherwise. *Fixed assets up*$_{(i,t-2)}$ is equal to 1 if the firms declare that their investments in fixed assets have increased, and 0 otherwise.[14]

The econometric results of our sensitivity analysis are displayed in Table 3. The evidence shows that, after having controlled for a number of potential sources of firm heterogeneity, the sign and the significance of our key variables remain stable across all specifications. Indeed, on one side, the use of internal funds, grants and informal financing and the VCBA ownership exert a positive impact on the probability to conduct product innovation. On the other side, the sensitive analysis confirms that there is no strong association between the probability to introduce a product innovation and the use of bank loans. This emerges from the sign of the marginal effects either negative (at 10% level) or not significant in model 1 and 2, respectively.

[Insert Table 3]

With regards to the firm-level controls their impact is noteworthy. Results show that the dummy *Profit up* is significant with a positive sign, indicating that firms reporting an increase in profits enjoy a higher likelihood to innovate. Interestingly, the variable *Labour up*, capturing the increase in the unit labour cost (cost of labour per unit of output), also displays a positive sign. This may indicate a positive relationship between productivity of labor (efficiency wage) and firm innovation efforts. Overall, the positive relation between innovation and some measures of firm performance provides support to the *self-selection* hypothesis and enriches the picture provided by Cassiman and Golovko (2011), who point to an interplay among innovation, productivity and trade internationalization.

The increase in a firm's creditworthiness (*Credit history up*) – signaling an increase in the firm's financial stability and trustworthiness – is relevant for financial contracts and, in turn, produces a positive effect on the firm's innovation efforts. Some interesting insights also emerge from the vector of the variable accounting for problems and constraints affecting firms. The coefficient of *Problem of finance* presents a significant and positive sign. Although, at the first

[14] As *Employees up*$_{it}$ and *Fixed assets up*$_{it}$, are available only from the 11-th to the 17-th waves, their use causes a drop in the number of observations.

inspection, the sign of the coefficient appears to be counterintuitive, it indicates that firms embarking in innovation activities might encounter difficulties and frictions in accessing finance, due to the asymmetric information and uncertainty of the innovation results.

The *Problem of finding customers* variable is positive, suggesting that firms attain a strategic advantage over competitors by developing and launching new products and services for the market. In such a case, innovation is the strategy to overcome this problem by searching for new market niches. Finally, the coefficient associated to *Problem of competition* has a negative sing and is significant across the specifications in Table 3. This might indicate that companies which declare an internal loss in efficiency and productivity display a lower likelihood to conduct innovation efforts.

Finally, as far firm growth is concerned, the positive marginal effects of *Employees up* and *Fixed assets up* show that firms experiencing size developments present a higher likelihood to introduce product innovation.

6. Conclusions

For SMEs, seeking external resources to finance innovation is not an easy task. The presence of information asymmetry associated with innovative activities unavoidably affects the investor–investee relations. This paper contributes to the literature that analyses the interplay between innovation and firm financing access. Despite the policy importance of this topic, the impact of the different sources of finance on firms' innovating efforts has remained largely unexplored.

We fill this gap by investigating the relevance of different financing channels (formal and informal), available for SMEs, to support their innovation efforts, after controlling for firm and country heterogeneity. Specifically, the study contributions are twofold. First, we analyse the effect of formal financing (bank) vs. internal resources, informal channels (family, friends) and public grants/subsidies. Second, we investigate how much of the probability to innovate can be attributed to individual heterogeneity and how much of it can reflect territorial features across Europe. To address these issues, we refer to MLMs, which allow us to exploit the hierarchical structure of data, with SMEs at the lowest level of the hierarchy and countries at the highest.

Based on firm-level data for a large sample of European SMEs, the main findings support the view that innovation is strongly affected by internal finance and grants or subsidies. Moreover, we document that firm-specific characteristics greatly affect individual propensity to innovate, while the country effect explains only about 4% of the variance of the firms' innovative behaviour.

The investigation has several implications.

First, it suggests that SMEs perceive tougher financial barriers in financing their innovative activities, and this induces them to use internal funds or search for alternative source of financing, such as grants/subsidies or informal channels such as friends and relatives. Public support is shown to be a useful tool to favour the firms' innovation efforts by relaxing the credit constraints that SMEs may face in their business.

Second, our study confirms the literature by finding that firms do not use the bank channel as a favourite source of financing innovation. Although regulators have attempted to reduce any friction in credit access (as in the case of the Basel agreements), and the EU has recently implemented a set of monetary and financial policies to sustain SMEs' access to credit, the inertial behaviour of agents might induce biased conducts which penalize SMEs when they invest in R&D. Reducing financial constraints and fostering innovation and growth opportunities for SMEs is of utmost importance in times of global competition and global distress in financial markets. For this purpose, the EU strategy for the 2020 objective is focused on building a knowledge-based economy where investments in R&D are crucial.

Recommendations for public policy to encourage long-term investment in intangibles would be another outcome of our investigation.

Finally, we acknowledge some data limitations given that SAFE provides information on firm localisation only at the country level. We believe that information at the provincial or regional level would add some value to our investigation provided that the local contexts in which the firms are embedded might affect the propensity to innovate and the firms' behaviour towards external financing. Addressing such limitations goes behind the scope of this analysis and opens the groundwork for future research.

References

Acharya, V., & Xu, Z. (2017). Financial dependence and innovation: The case of public versus private firms. *Journal of Financial Economics*, 124(2), 223-243.

Acharya, V. V., & Subramanian, K. V. (2009). Bankruptcy codes and innovation. *The Review of Financial Studies*, *22*(12), 4949-4988.

Acharya, V. V., Baghai, R. P., & Subramanian, K. V. (2013). Wrongful discharge laws and innovation. *The Review of Financial Studies*, *27*(1), 301-346.

Agénor, P. R., & da Silva, L. P. (2017). Cyclically adjusted provisions and financial stability. *Journal of Financial Stability*, *28*, 143-162.

Aghion, P., Bond, S., Klemm, A., & Marinescu, I. (2004). Technology and financial structure: are innovative firms different? *Journal of the European Economic Association*, *2*(2-3), 277-288.

Aiello, F., Pupo, V., & Ricotta, F. (2014). Explaining total factor productivity at firm level in Italy: Does location matter? *Spatial Economic Analysis*, *9*(1), 51-70.

Aiello, F. & Ricotta, F. (2016). Firm heterogeneity in productivity across Europe: evidence from multilevel models. *Economics of Innovation and New Technology*, 25(1), 57-89,

Arrow, K., (1962). *Economic welfare and the allocation of resources for invention*. In: Nelson, R. (Ed.), The Rate and Direction of Inventive Activity: Economic and Social Factors. Princeton University Press, pp. 609–625.

Ayyagari, M., Demirgüç-Kunt, A., & Maksimovic, V. (2011). Firm Innovation in Emerging Markets: The Role of Finance, Governance, and Competition. *Journal of Financial and Quantitative Analysis*, 46(6), 1545-1580.

Bah, R., & Dumontier, P. (2001). R&D intensity and corporate financial policy: Some international evidence. *Journal of Business Finance & Accounting*, *28*(5-6), 671-692.

Baker, M., & Wurgler, J. (2002). Market timing and capital structure. *The journal of finance*, *57*(1), 1-32.

Baldwin, R. E., & Okubo, T. (2005). Heterogeneous firms, agglomeration and economic geography: spatial selection and sorting. *Journal of Economic Geography*, *6*(3), 323-346.

Beugelsdijk, S. (2007). The regional environment and a firm’s innovative performance: a plea for a multilevel interactionist approach. *Economic Geography*, *83*(2), 181-199.

Bhattacharya, U., Hsu, P. H., Tian, X., & Xu, Y. (2017). What affects innovation more: Policy or policy uncertainty? *Journal of Financial and Quantitative Analysis*, *52*(5), 1869-1901.

Bickel, R. (2007). *Multilevel analysis for applied research: It's just regression!* Guilford Press.

Bond, S., Elston, J.A, Mairesse. J. & Mulkay, B. (2003). “Financial Factors and Investment in Belgium, France, Germany, and the United Kingdom: a Comparison Using Firm Panel Data”, *The Review of Economics and Statistics* vol. 85, N. 1.

Bond, S., Harhoff, D. & Van Reenen,J. (1999). “Investment, R&D and Financial Constraints in Britain and Germany”, *The Institute for Fiscal Studies Working Paper* W99/5, 1999.

Bougheas, S., Görg, H., & Strobl, E. (2003). Is R & D financially constrained? Theory and evidence from Irish manufacturing. *Review of Industrial Organization*, *22*(2), 159-174.

Brown, J. R., Martinsson, G., & Petersen, B. C. (2012). Do financing constraints matter for R&D?. *European Economic Review*, *56*(8), 1512-1529.

Brown, J. R., Martinsson, G., & Petersen, B. C. (2013). Law, stock markets, and innovation. *The Journal of Finance*, *68*(4), 1517-1549.

Carbo-Valverde, S., Degryse, H., & Rodríguez-Fernández, F. (2015). The impact of securitization on credit rationing: Empirical evidence. *Journal of Financial Stability*, *20*, 36-50.

Cassiman, B., & Golovko, E. (2011). Innovation and internationalization through exports. *Journal of International Business Studies*, *42*(1), 56-75.

Castellacci, F. (2007). Technological regimes and sectoral differences in productivity growth. *Industrial and corporate change*, *16*(6), 1105-1145.

Chiao, C. (2002). Relationship between debt, R&D and physical investment, evidence from US firm-level data. *Applied Financial Economics*, *12*(2), 105-121.

Cornaggia, J., Mao, Y., Tian, X., & Wolfe, B. (2015). Does banking competition affect innovation? *Journal of financial economics*, *115*(1), 189-209.

Cosh, A., Cumming, D., & Hughes, A. (2009). Outside enterpreneurial capital. *The Economic Journal*, *119*(540), 1494-1533.

Cowan, K., Drexler, A., & Yañez, Á. (2015). The effect of credit guarantees on credit availability and delinquency rates. *Journal of Banking & Finance*, *59*, 98-110.

David, P. A., Hall, B. H., & Toole, A. A. (2000). Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. *Research policy*, *29*(4-5), 497-529.

Dixit, A. K., & Pindyck, R. S. (1994). *Investment under uncertainty*. Princeton University Press.

Dosi, G, Nelson, R.R. (2010). Technical change and industrial dynamics as evolutionary processes. In: Hall, B., Rosenberg, N. (Eds.) Handbook of the economics of innovation. North Holland, London.

Fazio, G., & Piacentino, D. (2010). A Spatial Multilevel Analysis of Italian SMEs' Productivity. *Spatial Economic Analysis*, *5*(3), 299-316.

Fazzari, S. M., Hubbard, R. G., Petersen, B. C., Blinder, A. S., & Poterba, J. M. (1988). Financing constraints and corporate investment. Brookings papers on economic activity, 1, 141-206.

Fischer, E. O., Heinkel, R., & Zechner, J. (1989). Dynamic capital structure choice: Theory and tests. *The Journal of Finance*, *44*(1), 19-40.

García-Quevedo, J., Segarra-Blasco, A., & Teruel, M. (2018). Financial constraints and the failure of innovation projects. *Technological Forecasting and Social Change*, *127*, 127-140.

Goldstein, H. (2003). *Multilevel statistical models*. Arnold, London.

Griliches, Z. (1995). R&D and productivity: economic results and measurement issues. *Handbook of the Economics of Innovation and Technological Change, Blackwell, Oxford*, 52-89.

Guariglia, A., & Liu, P. (2014). To what extent do financing constraints affect Chinese firms' innovation activities? *International Review of Financial Analysis*, 36, 223-240.

Hall, B. H. (1992). *Investment and research and development at the firm level: does the source of financing matter?* (No. w4096). National bureau of economic research.

Hall, B. H. (1994). Corporate restructuring and investment horizons in the United States, 1976–1987. *Business History Review*, *68*(1), 110-143.

Hall, B. H. (2002). The financing of research and development. *Oxford review of economic policy*, *18*(1), 35-51.

Hall, B. H., & Lerner, J. (2010). The financing of R&D and innovation. In *Handbook of the Economics of Innovation* (Vol. 1, pp. 609-639). North-Holland.

Harhoff, D. (1998). "Are There Financing Constraints in German Manufacturing Firms?", *Annales d'économie et de statistique*, n. 49/50, 1998.

Heck, R.H., Thomas, S.L. (2000). *An introduction to multilevel modelling techniques*. Lawrence Erlbaum Associates, Mahwah, New Jersey

Himmelberg, C. P., & Petersen, B. C. (1994). R & D and internal finance: A panel study of small firms in high-tech industries. *The Review of Economics and Statistics*, 38-51.

Hottenrott, H., & Peters, B. (2012). Innovative capability and financing constraints for innovation: More money, more innovation? *Review of Economics and Statistics*, *94*(4), 1126-1142.

Hox J.J. (2002). *Multilevel analysis: techniques and applications*. Lawrence Erlbaum Associates, Mahwah, New Jersey.

Hsu, P. H., Tian, X., & Xu, Y. (2014). Financial development and innovation: Cross-country evidence. *Journal of Financial Economics*, *112*(1), 116-135.

Kerr, W. R., & Nanda, R. (2015). Financing innovation. *Annual Review of Financial Economics*, *7*, 445-462.

Kraus, A., & Litzenberger, R. H. (1973). A state‐preference model of optimal financial leverage. *The journal of finance*, *28*(4), 911-922.

Luke, D.A. (2004). *Multilevel Modelling*. Sage, London.

Maas, C. J., & Hox, J. J. (2004). Robustness issues in multilevel regression analysis. *Statistica Neerlandica*, *58*(2), 127-137.

Mateut, S. (2018). Subsidies, financial constraints and firm innovative activities in emerging economies. *Small Business Economics*, *50*(1), 131-162.

Mahlberg, B., I. Freund, J. Crespo Cuaresma, & A. Prskawetz. (2013). The age-productivity pattern: Do location and sector affiliation matter? *Journal of the Economics of Ageing*, http://dx.doi.org/10.1016/j.jeoa.2013.08.002.

Meuleman, M., & De Maeseneire, W. (2012). Do R&D subsidies affect SMEs' access to external financing?. *Research Policy*, *41*(3), 580-591.

Mina, A., Lahr, H., & Hughes, A. (2013). The demand and supply of external finance for innovative firms. *Industrial and Corporate Change*, *22*(4), 869-901.

Modigliani, F., & Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. *The American economic review*, *48*(3), 261-297.

Mulkay, B., Hall, B. H., & Mairesse, J. (2001). Firm level investment and R&D in France and the United States: A comparison. In *Investing today for the world of tomorrow* (pp. 229-273). Springer, Berlin, Heidelberg.

Myers, S. C. (1984). The capital structure puzzle. *The journal of finance*, *39*(3), 574-592.

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of financial economics*, *13*(2), 187-221.

Nelson, R. R. (1959). The simple economics of basic scientific research. *Journal of political economy*, *67*(3), 297-306.

Nickell, S., & Nicolitsas, D. (1999). How does financial pressure affect firms? *European Economic Review*, 43(8), 1435-1456.

Opler, T. C., & Titman, S. (1994). Financial distress and corporate performance. *The Journal of Finance*, *49*(3), 1015-1040.

Paul, J., Parthasarathy, S., & Gupta, P. (2017). Exporting challenges of SMEs: A review and future research agenda. *Journal of World Business*, *52*(3), 327-342.

Pigini, C., Presbitero, A. F., & Zazzaro, A. (2016). State dependence in access to credit. *Journal of financial stability*, *27*, 17-34.

Pindyck, R. S. (1993). Investments of uncertain cost. *Journal of financial Economics*, *34*(1), 53-76.

Popov, A., & Udell, G. F. (2012). Cross-border banking, credit access, and the financial crisis. *Journal of international economics*, *87*(1), 147-161.

Popov, A., & Van Horen, N. (2014). Exporting sovereign stress: Evidence from syndicated bank lending during the euro area sovereign debt crisis. *Review of Finance*, *19*(5), 1825-1866.

Rabe-Hesketh, S., & Skrondal, A. (2008). *Multilevel and longitudinal modeling using Stata*. STATA press.

Rajan, R. G., & Zingales, L. (2001). Financial systems, industrial structure, and growth. *Oxford review of economic Policy*, *17*(4), 467-482.

Raspe, O., & van Oort, F. G. (2011). Firm heterogeneity, productivity and spatially bounded knowledge externalities. *Socio-Economic Planning Sciences*, *45*(1), 38-47.

Raudenbush, S.W., & Bryk, A.S. (2002). *Hierarchical Linear Models: Applications and data analysis methods* (2nd ed.). Thousand Oaks, CA: Sage Publications.

Richter, T. (2006). "What is wrong with ANOVA and multiple regression? Analyzing sentence reading times with hierarchical linear models", *Discourse Processes*, 41(3), 221-250.

Romer, P. (1990). Endogenous technological change. *Journal of Political Economy*, 98, S71–S102.

Ross, S. A. (1977). The determination of financial structure: the incentive-signalling approach. *The bell journal of economics*, 23-40.

Sasidharan, S., Lukose, P. J., & Komera, S. (2015). Financing constraints and investments in R&D: Evidence from Indian manufacturing firms. *The Quarterly Review of Economics and Finance*, 55, 28-39.

Schumpeter, J. A. (1934). Change and the Entrepreneur. *Essays of JA Schumpeter*.

Snijders, T. A., & Berkhof, J. (2008). Diagnostic checks for multilevel models. In *Handbook of multilevel analysis* (pp. 141-175). Springer, New York, NY.

Srholec, M. (2010). Multilevel Approach to Geography of Innovation. *Regional Studies*, 44: 1207-1220.

Srholec, M. (2015). Understanding the Diversity of Cooperation on Innovation across Countries. *Economics of Innovation and New Technology*, 24 (1-2): 159-182.

Steele, F. (2008). Multilevel models for longitudinal data. *Journal of the Royal Statistical Society: series A (statistics in society)*, *171*(1), 5-19.

Stiglitz, J. & Weiss, A. (1981). Credit rationing in markets with imperfect information. *American Economic Review* 71 (3), 393–410.

Tyagi, R. K. (2006). New product introductions and failures under uncertainty. *International Journal of Research in Marketing*, *23*(2), 199-213.

Table 1. Descriptive statistics for variables included in the estimated models

Variables	Observations	Mean	Std. Dev.	Min	Max
Product innovation	24,663	0.3434	0.4748	0	1
Use Internal Funds$_{(i,t-2)}$	24,663	0.2363	0.4248	0	1
Use Bank Loans$_{(i,t-2)}$	24,663	0.2684	0.4431	0	1
Use Bank Credit$_{(i,t-2)}$	24,663	0.5314	0.4990	0	1
Use Grants or Subsidies$_{(i,t-2)}$	24,663	0.1210	0.3261	0	1
Use Family or Friends Loans$_{(i,t-2)}$	24,663	0.1147	0.3187	0	1
Use Equity$_{(i,t-2)}$	24,663	0.0341	0.1814	0	1
VCBA	24,663	0.0063	0.0790	0	1
Public company	24,663	0.0265	0.1606	0	1
Single owner	24,663	0.2904	0.4539	0	1
Family	24,663	0.4977	0.5000	0	1
Small	24,663	0.4393	0.4963	0	1
Medium sized	24,663	0.4562	0.4981	0	1
Large	24,663	0.0936	0.2913	0	1
Very old	24,663	0.8438	0.3631	0	1
Old	24,663	0.1077	0.3099	0	1
Medium aged	24,663	0.0358	0.1859	0	1
Young	24,663	0.0075	0.0861	0	1
Industry	24,663	0.2642	0.4409	0	1
Construction	24,663	0.1001	0.3001	0	1
Trade	24,663	0.2400	0.4271	0	1
Services	24,663	0.3354	0.4721	0	1

Source: our elaborations on data from SAFE.

Table 2. Estimated marginal effects from MLM probit.
The empty model and the baseline specifications

VARIABLES	Empty model 1	Model 2	Model 3	Model 4
Firm level				
Use Internal Funds$_{(i,t-2)}$		0.0369 ***	0.0349 ***	0.0301 ***
Use Bank Loans$_{(i,t-2)}$		-0.0057	-0.0048	-0.0053
Use Grants or Subsidies$_{(i,t-2)}$		0.0836 ***	0.0825 ***	0.0729 ***
Use Family or Friends Loans$_{(i,t-2)}$		0.0431 ***	0.0393 ***	0.0412 ***
Use Equity$_{(i,t-2)}$		0.0584 ***	0.0526 ***	0.0529 ***
VCBA			0.1285 ***	0.1080 ***
Public company			0.0781 ***	0.0738 ***
Single owner			-0.0388 ***	-0.0180 *
Family			-0.0312 ***	-0.0185 **
Time Effect	No	No	No	Yes
Size Effect	No	No	No	Yes
Age Effect	No	No	No	Yes
Sector Effect	No	No	No	Yes
Country level				
Var(Random intercept)	0.0340 ***	0.0340 ***	0.0343 ***	0.0354 ***
Observations	24,663	24,663	24,663	24,663
Number of groups	20	20	20	20
Log likelihood	-15701	-15624	-15591	-15295
Chi-squared	326.4	335.6	336.5	334.9
ICC country	3.29%	3.29%	3.31%	3.42%

Source: our elaborations on data from SAFE.
Dependent variable: Product Innovation.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

ICC country = $\frac{\sigma_{\mu 0}^2}{\sigma_{\mu 0}^2+\sigma_e^2}$, where $\sigma_{\mu 0}^2$ is the so-called between group variance and σ_e^2 is the so-called within group variance.

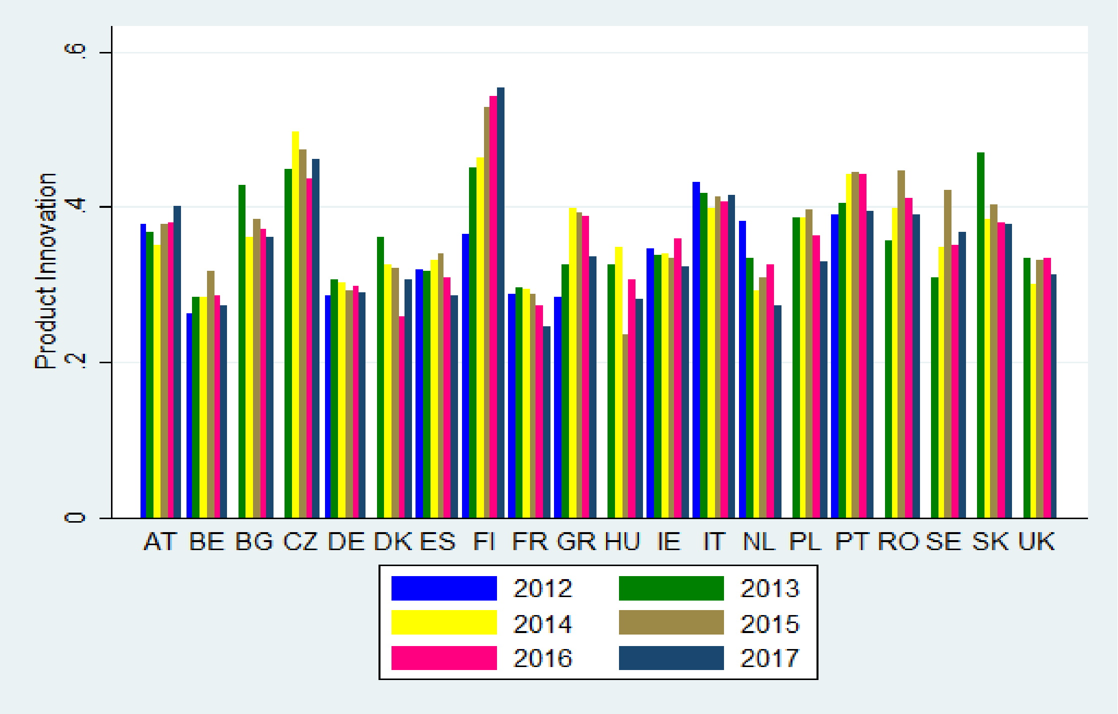
ICC measures the proportion of total variance “explained” by the grouping structure, i.e. the intra-class correlation for our second level of analysis, i.e. country.

Table 3. Estimated marginal effects from MLM probit. A sensitivity analysis

VARIABLES	Model 1		Model 2	
Firm level				
Use Internal Funds$_{(i,t-2)}$	0.0241	***	0.0218	**
Use Bank Loans$_{(i,t-2)}$	-0.0132	*	-0.0143	
Use Grants or Subsidies$_{(i,t-2)}$	0.0653	***	0.0495	***
Use Family or Friends Loans$_{(i,t-2)}$	0.0415	***	0.0440	***
Use Equity$_{(i,t-2)}$	0.0610	***	0.0756	***
VCBA	0.1134	***	0.1515	***
Public company	0.0723	***	0.0692	***
Single owner	-0.0226	**	-0.0186	
Family	-0.0273	***	-0.0251	**
Profit up$_{(i,t-2)}$	0.0428	***	0.0313	***
Cost of Labour up$_{(i,t-2)}$	0.0328	***	0.0213	**
Other cost up$_{(i,t-2)}$	0.0091		0.0109	
Interest expenses up$_{(i,t-2)}$	0.0105		0.0080	
Leverage up$_{(i,t-2)}$	0.0051		-0.0056	
Credit history up$_{(i,t-2)}$	0.0450	***	0.0323	***
Problem of finance$_{(i,t-2)}$	0.0261	***	0.0363	***
Problem of cost of production$_{(i,t-2)}$	-0.0054		-0.0109	
Problem of availability skilled staff$_{(i,t-2)}$	0.0298	***	0.0268	**
Problem of finding customer$_{(i,t-2)}$	0.0221	***	0.0303	***
Problem of regulation$_{(i,t-2)}$	0.0131	*	0.0070	
Problem of competition$_{(i,t-2)}$	-0.0281	***	-0.0278	***
Employees up$_{(i,t-2)}$			0.0482	***
Fixed assets up$_{(i,t-2)}$			0.0695	***
Time/Size/Age/Sector effects	Yes		Yes	
Country level				
Var(Random intercept)	0.0383	***	0.0441	***
Observations	21,654		15,623	
Number of groups	20		20	
Log likelihood	-13332		-9609	
Chi-squared	325.2		269.5	
ICC country	3.69%		4.22%	

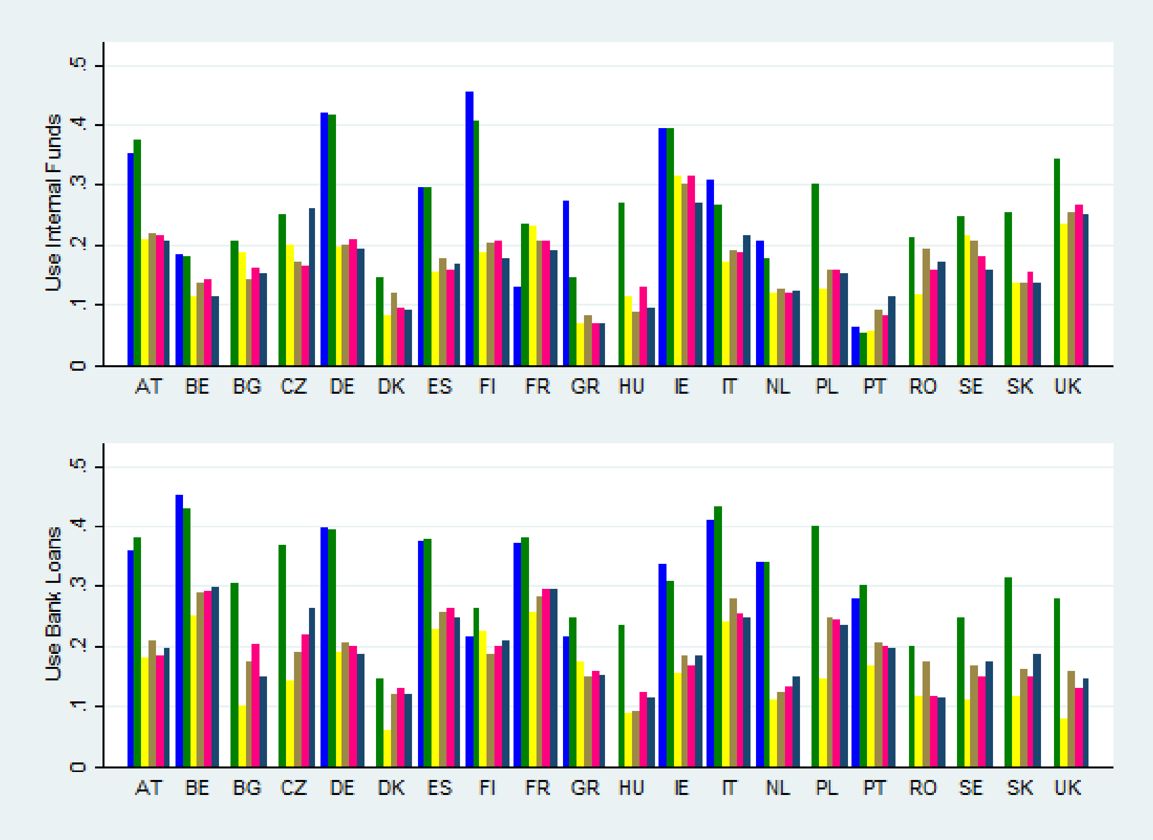
Source: our elaborations on data from SAFE.
Dependent variable: Product Innovation. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.
ICC country: see table 2.

Figure 1. Proportion of product innovators in the sample, by country and year



Legend: AT=Austria, BE=Belgium, BG=Bulgaria, CZ=Czech Republic, DE=Germany, DK=Denmark, ES=Spain, FI=Finland, FR=France, GR=Greece, HU=Hungary, IE=Ireland, IT=Italy, NL=Netherlands, PL=Poland, PT=Portugal, RO=Romania, SE=Sweden, SK=Slovakia, UK=United Kingdom.
Source: our elaborations on data from SAFE.

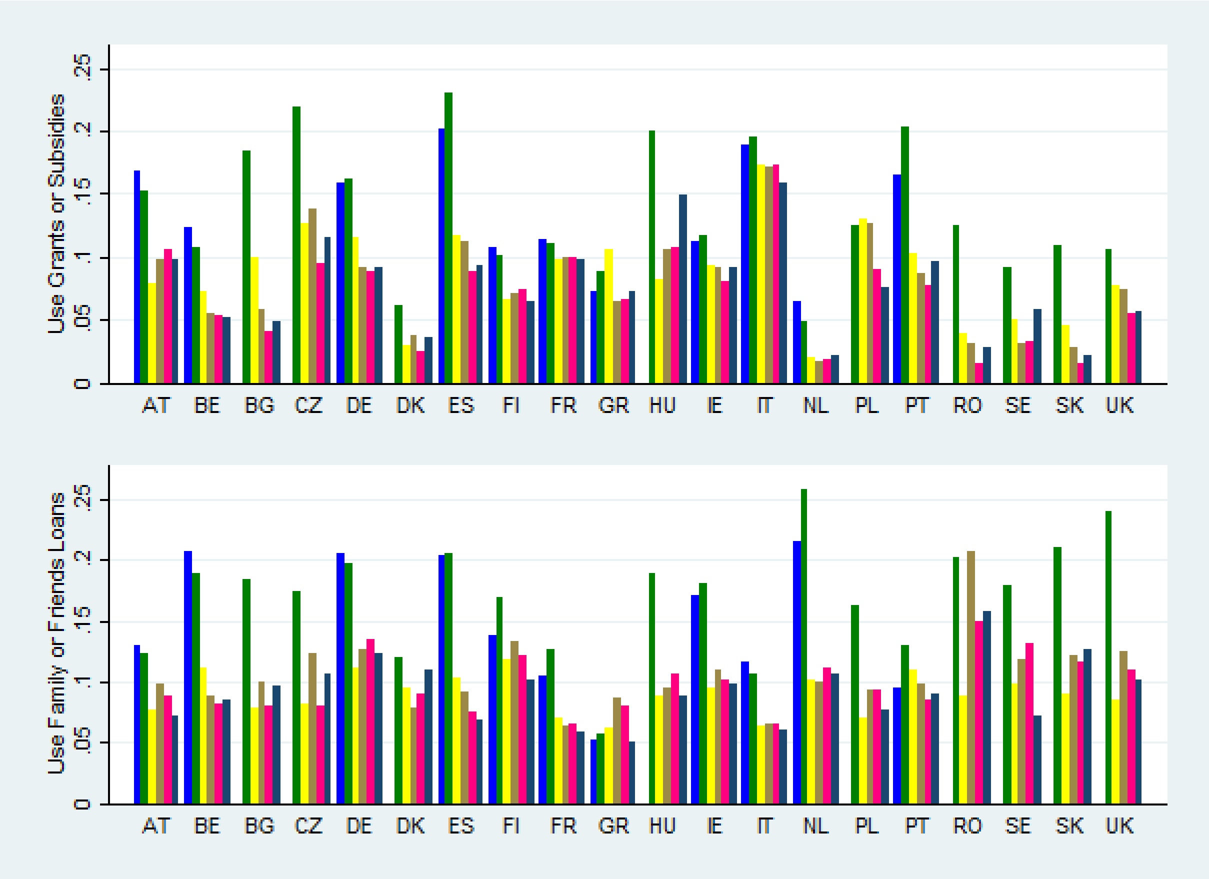
Figure 2. Proportion of firms using Internal funds and Bank loans, by country and year from 2012 to 2017



Legend: AT=Austria, BE=Belgium, BG=Bulgaria, CZ=Czech Republic, DE=Germany, DK=Denmark, ES=Spain, FI=Finland, FR=France, GR=Greece, HU=Hungary, IE=Ireland, IT=Italy, NL=Netherlands, PL=Poland, PT=Portugal, RO=Romania, SE=Sweden, SK=Slovakia, UK=United Kingdom.

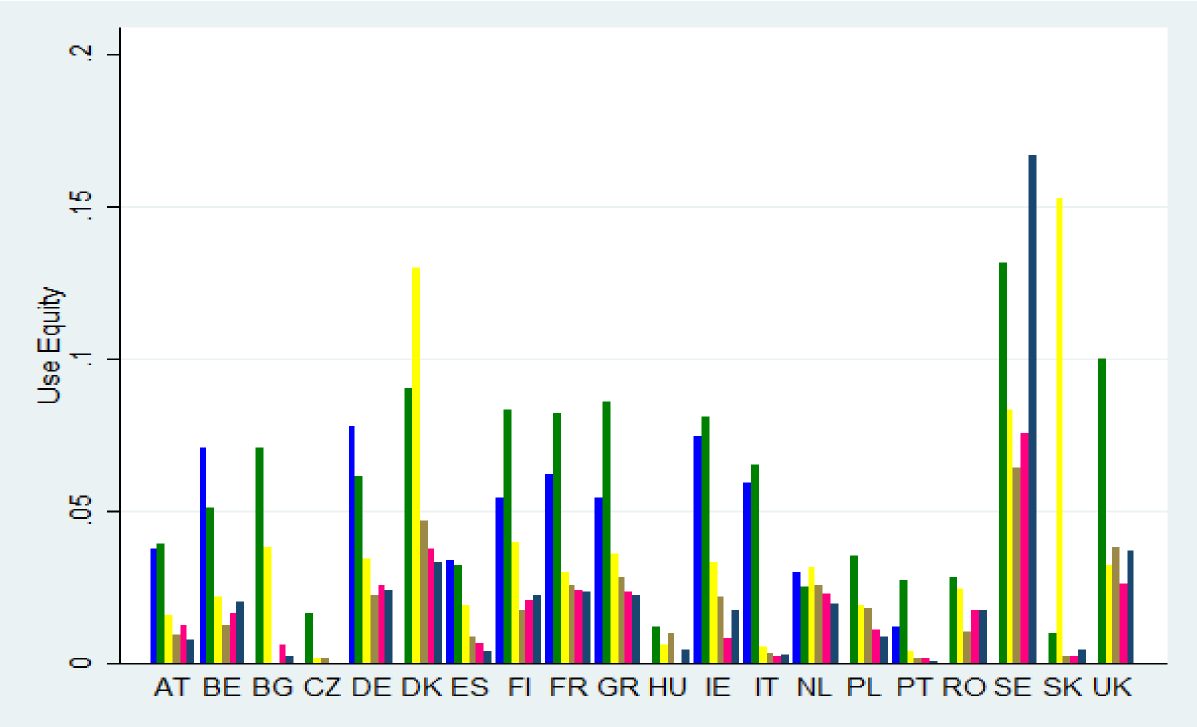
Source: our elaborations on data from SAFE.

Figure 3. Proportion of firms using Informal loans and Grants, by country and year from 2012 to 2017



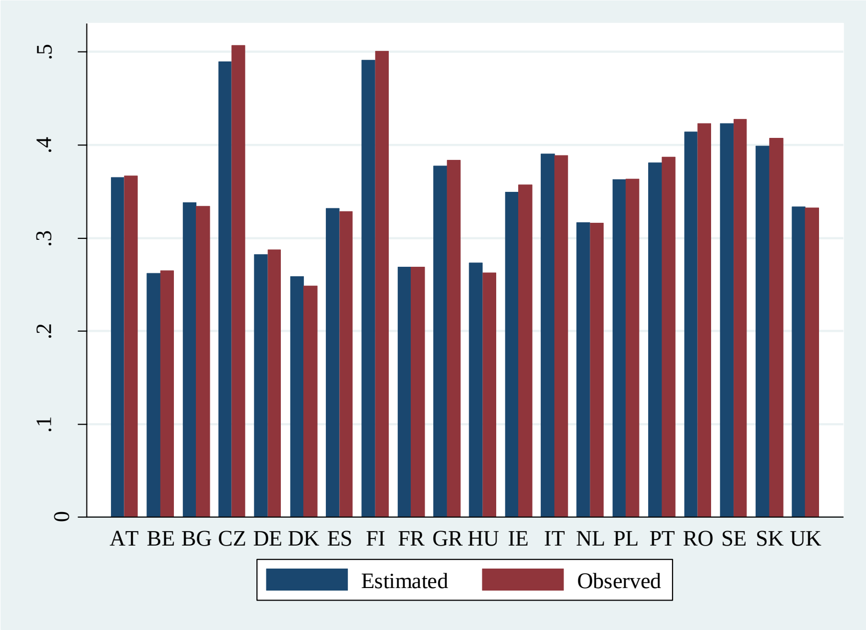
Legend: AT=Austria, BE=Belgium, BG=Bulgaria, CZ=Czech Republic, DE=Germany, DK=Denmark, ES=Spain, FI=Finland, FR=France, GR=Greece, HU=Hungary, IE=Ireland, IT=Italy, NL=Netherlands, PL=Poland, PT=Portugal, RO=Romania, SE=Sweden, SK=Slovakia, UK=United Kingdom.
Source: our elaborations on data from SAFE.

Figure 4. Proportion of firms using Equity, by country and year from 2012 to 2017



Legend: AT=Austria, BE=Belgium, BG=Bulgaria, CZ=Czech Republic, DE=Germany, DK=Denmark, ES=Spain, FI=Finland, FR=France, GR=Greece, HU=Hungary, IE=Ireland, IT=Italy, NL=Netherlands, PL=Poland, PT=Portugal, RO=Romania, SE=Sweden, SK=Slovakia, UK=United Kingdom.
Source: our elaborations on data from SAFE.

Figure 5. Comparing the observed proportion of innovator and the estimated probability to innovate (averaging by country and years).



Legend: AT=Austria, BE=Belgium, BG=Bulgaria, CZ=Czech Republic, DE=Germany, DK=Denmark, ES=Spain, FI=Finland, FR=France, GR=Greece, HU=Hungary, IE=Ireland, IT=Italy, NL=Netherlands, PL=Poland, PT=Portugal, RO=Romania, SE=Sweden, SK=Slovakia, UK=United Kingdom.

Source: our elaborations on data from SAFE.

Note: Data refer to the model 3 of Table 2

Appendix

Table A1 Distribution of firms by country

Country name	Frequency	Percentage
Austria	1,197	4.85
Belgium	955	3.87
Bulgaria	380	1.54
Czech Republic	353	1.43
Denmark	427	1.73
Finalnd	980	3.97
France	2,951	11.97
Germany	2,797	11.34
Greece	1,094	4.44
Hungary	366	1.48
Ireland	1,131	4.59
Italy	3,431	13.91
Netherlands	1,450	5.88
Poland	1,076	4.36
Portugal	1,010	4.1
Romania	364	1.48
Slovakia	508	2.06
Spain	2,760	11.19
Sweden	402	1.63
United Kingdom	1,031	4.18
Total	24,663	100

Source: our elaborations on data from SAFE.

Table A2. Descriptive statistics of additional variables for sensitivity analysis

Variables	Observations	Mean	Std. Dev.	Min	Max
Profit up$_{(i,t-2)}$	23,163	0.3205	0.4667	0	1
Cost of Labour up$_{(i,t-2)}$	23,163	0.5148	0.4998	0	1
Other cost up$_{(i,t-2)}$	23,163	0.5112	0.4999	0	1
Interest expenses up$_{(i,t-2)}$	23,163	0.2086	0.4063	0	1
Leverage up$_{(i,t-2)}$	23,163	0.1729	0.3782	0	1
Credit history up$_{(i,t-2)}$	23,163	0.2730	0.4455	0	1
Employees up$_{(i,t-2)}$	16,012	0.2786	0.4483	0	1
Fixed assets up$_{(i,t-2)}$	16,012	0.2963	0.4566	0	1
Problem of finance$_{(i,t-2)}$	21,654	0.1532	0.3602	0	1
Problem of cost of production$_{(i,t-2)}$	21,654	0.1721	0.3775	0	1
Problem of availability skilled staff$_{(i,t-2)}$	21,654	0.1741	0.3792	0	1
Problem of finding customer$_{(i,t-2)}$	21,654	0.5544	0.4970	0	1
Problem of regulation$_{(i,t-2)}$	21,654	0.4239	0.4942	0	1
Problem of competition$_{(i,t-2)}$	21,654	0.5072	0.5000	0	1

Source: our elaborations on data from SAFE.