External financing of innovative small and medium enterprises (SMEs): unpacking bank credit with respect to innovation typologies and combinations

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Abstract

We investigate the extent to which small and medium enterprises' (SMEs) external financing varies with the innovation profiles they reveal in terms of introduced and combined innovation typologies. Using Survey on the Access to Finance of Enterprises data, we address this research issue with respect to 11 European countries over the 2014–2019 period and overcome the context specificity of previous analyses. Results suggest that the innovative profile of SMEs is responsible for several nuances in both their demand for and supply of bank loans. Being an innovator increases SMEs' credit requests, but this demand increases also and above all with their involvement in specific innovation typologies and combinations. Having an innovative profile of nearly any type does not lead SMEs to refrain from demanding bank loans because of a fear of rejection, but a wide involvement in specific innovation types reduces the chance that their internal funds make them refrain from asking for credit. Innovative SMEs are significantly more likely to be credit-constrained than non-innovative ones, but the probability of not receiving bank loans increases only for firms that combine specific innovation typologies. An innovation status of SMEs makes banks more selective in their decision to completely fulfill a credit request, but the probability of this decision decreases only with respect to a few, multi-innovation profiles. The extent to which SMEs innovate in different domains, rather than the simple innovation intensity, appears to be a crucial dimension to consider in future research and in devising policies to attenuate financial constraints to innovation.

JEL classification: G32, O16, O30

1. Introduction

A long-lasting research line already exists regarding the relationship between innovation and finance at the firm level (Hall *et al.*, 2016). Furthermore, interest in the topic has been reinvigorated by the financial and economic crises of the last decade, by the high degree of financialization of economic systems these crises have revealed (Mazzucato, 2013), as well as by the recession provoked by the coronavirus disease-19 pandemic. In particular, the credit shortage entailed in times of crisis has drawn novel attention to the problematic financing of already innovative firms and especially small and medium enterprises (SMEs) (Czarnitzki, 2006; Freel, 2007; Bellucci *et al.*, 2014; Lee *et al.*, 2015; Lee and Brown, 2016; Hain and Christensen, 2020).

In spite of intense research efforts, the results regarding the external financing of innovative firms generally, and SMEs in particular, are far from conclusive. On the supply side, contrasting theoretical arguments have been developed, and mixed country-specific empirical results have been obtained regarding the alleged disadvantages innovative firms experience in obtaining external finance (Canepa and Stoneman, 2007; Freel, 2007; Mina *et al.*, 2013; Bellucci *et al.*, 2014; Brancati, 2015; Hain and Christensen, 2020; Montresor and Vezzani, 2021). On the demand side, research has been thinner and even more inconclusive regarding the hypothesis that innovative SMEs are more in need of external finance than non-innovative ones, rather than being instead discouraged in the search for it (Mina *et al.*, 2013; Lee *et al.*, 2015; Lee and Brown, 2016). An important share of the heterogeneity in results is due to the context specificity of the research, to overcome which more general multi-country studies would be desirable. However, the heterogeneous accuracy with which firm innovation is considered in these studies is also relevant. The majority refer to research and development (R&D) expenditures and/or patents when measuring innovation (Canepa and Stoneman, 2007; Savignac, 2008), and in spite of the wider availability and codifiability of these types of data, these studies are incapable of disentangling the specific nature of the relative innovation outcome, e.g., product vs. process innovations or radical vs. incremental ones. A few recent studies have instead resorted to survey data and, in spite of the response biases they can suffer from, have shown that the particular type of innovations that SMEs introduce does make a difference for both credit demand and supply (e.g., Mina *et al.*, 2013; Hain and Christensen, 2020). However, this issue has only been partially addressed. On the one hand, the spectrum of innovators that face financing problems among SMEs is much wider and heterogeneous than that hitherto addressed by the extant literature, especially in light of the different combinations of innovation typologies to which firms can resort. Indeed, firms often combine innovation types (Agwu *et al.*, 2020) and innovate in a complex way across technological (product and process) and non-technological (organizational and marketing) domains (Evangelista and Vezzani, 2010, 2012). On the other hand, the features and channels through which these different innovation typologies (and combinations thereof) can affect the external credit of firms (and SMEs) have been only superficially addressed and deserve closer scrutiny.

The present paper aims to fill this research gap in three respects. First of all, we look at whether innovative SMEs differ from non-innovative ones in their access to external finance, not only by distinguishing different types of innovation (product, process, marketing, and organizational), as some previous studies have already done (see Section 2), but also by considering their possible combinations—that is, by distinguishing the different configurations of finance-seeking innovative SMEs that emerge by looking at the combinations of innovation typologies they introduce. In brief, we augment previous analyses of multiple innovation measures by looking also at the complexity that derives from combined innovation measures. Second, we investigate whether innovative SMEs can be distinguished from non-innovative ones, not only in the extent to which they seek and obtain external finance (or not) but also in terms of the reasons for applying and the amounts received, respectively. Third, by merging different waves of the Survey on the Access to Finance of Enterprises (SAFE) by the European Commission and the European Central Bank, we address these research questions with respect to as many as 11 European Union (EU) countries over the 2014–2019 period and obtain results amenable to a wider generalization.

Results suggest that an innovative profile could be responsible for several nuances in both the demand and supply of bank loans to SMEs. Being an innovator raises an SME's credit demand, but this demand increases also and above all with their involvement in specific innovation typologies and combinations of these. Having an innovative profile (of nearly any type) does not lead SMEs to refrain more from requesting credit because of a fear of rejection, but a wide involvement in specific innovation types reduces the chance that their internal funds make them refrain from asking for external credit. Generically innovative SMEs are significantly more likely to be credit-constrained than non-innovative ones, but the probability of not receiving credit increases only for firms involved in innovation to an extensive margin, specifically by combining specific innovation typologies. A generic innovation status of SMEs apparently makes banks more selective in the decision to completely fulfill a credit request, but the probability of this decision increases only with respect to a few, mainly multi-innovation profiles. Overall, the extent to which SMEs innovate in different and/or multiple domains—rather than the simple intensity of their innovation—appears to be a crucial dimension to consider in future research and in devising policies to attenuate the financial constraints to innovation.

The rest of the paper is structured as follows. Section 2 positions the paper among the existing literature. Section 3 illustrates the empirical application, and Section 4 presents the results. Section 5 concludes with policy implications, limitations, and opportunities for future research.

2. Background literature

In spite of the pessimistic views of the initial papers on the topic, innovative firms resorting to bank finance has not been as prohibitive and rare as initially predicted (Brown *et al.*, 2009). On the contrary, external sources of finance appear common among innovators, as well as their use of patents (Hall, 2019) and intellectual property rights as collateral to access them (for a review of this evidence, see Kerr and Nanda, 2015).[1]

In the case of innovative SMEs, however, external financing reveals several obstacles that could be responsible for the insufficiency of their funds to take advantage of potentially profitable investment opportunities (Cosh *et al.*, 2009). In the existing literature, this alleged "finance gap" has been mainly addressed by looking at the credit that innovative SMEs (and innovative firms in general) receive from banks (or not)—that is, at the *supply* end of credit. The analysis of their credit *demand* is instead still scant, but interesting results have been obtained with respect to which we need to position the current work. While previous research has in some cases distinguished between product and process innovations, and more rarely between incremental and radical ones, to the best of our knowledge no studies exist that investigate the possible combined use that firms can make of different innovation typologies. As we will argue, this combination brings to the fore the effect that complexity in innovation can be expected to have on firms' external financing.

2.1 Credit supply to (different kinds of) innovative SMEs

The fact that innovative firms can easily end up being credit rationed has been widely investigated in the academic literature (for a review, see Kerr and Nanda, 2015). Several studies have identified a set of factors that render lenders more alert, and less effective, in evaluating the risk/return profiles of prospective innovative investments, with the inherent uncertainty and difficult collateralization of R&D projects, the idiosyncratic distribution of innovation payoffs, and the asymmetric information between innovators and financiers being the most relevant. Because of these factors, the cost of external financing for innovators turns out to be higher than for non-innovators. The extent to which innovative firms (and SMEs in particular) can access credit thus decreases, and some of their potentially profitable innovative projects may remain uncompleted (Hall *et al.*, 2016).

The above-mentioned finance-inhibiting factors are usually listed in rapid sequence as pertaining to innovation in general, but their incidence is arguably variable across different innovation typologies. To give just a few examples, radical innovations are usually more uncertain than incremental ones, and the degree of novelty and risk is inherently higher for new products as opposed to new processes (Murat and Baki, 2011). Looking at another financing barrier, organizational and marketing innovations are more inherently intangible than technological ones and thus hardly guaranteed by proper collateral (Laforet, 2011).

Because of these differences, in the few studies that have considered it, the typology of innovation has been found to matter in accounting for the credit rationing of innovative SMEs. This is the case for a stream of research on the financing of British SMEs, which shows that although there are both temporal (e.g., before and after the crisis; Freel, 2007; Lee *et al.*, 2015) and geographical nuances (e.g., between core and peripheral regions; Lee and Brown, 2016), it is product rather process innovation that makes them credit rationed, in particular when the innovation is radical rather than simply incremental.

1 Empirical evidence also reveals that while not infrequent, innovators resorting to debt financing is nevertheless "secondary" with respect to other means of financing and is consistent with the so-called "pecking order theory" of finance (Myers and Majluf, 1984; Myers, 2000), which we discuss in Section 2.2.

Similar results are obtained by Hain and Christensen (2020) with respect to a sample of small and medium Danish firms over the 2000–2013 period. Controlling for non-linear credit-rationing effects, out of the firms that have sought external financing, radical innovators show greater chances of experiencing credit constraints than incremental innovators. Conversely, the alleged credit rationing of innovative SMEs is reversed in the comparative study of UK and US firms (2002–2004) by Mina *et al.* (2013). Unlike input variables of innovation (such as R&D, which is revealed to be non-significant), output variables in the form of introduced product and process innovations actually increase rather than decrease the chances of receiving credit (especially for US firms). As the authors suggest, this result points to another set of financing issues that counteract the innovator financial-gap thesis. Overall, these factors refer to the positive "signaling effects" that innovative firms—unlike non-innovative ones—can exert on lenders, being perceived by them as capable of achieving high returns from their R&D projects (Coad and Rao, 2008). Firms' innovation would also signal their capacity of obtaining a costly recognition of their inventive activities in terms of IPR (Hottenrott *et al.*, 2016; Hall, 2019) and when relevant their capacity of passing the screening that public authorities implement prior to allowing R&D grants or subsidies (Howell, 2017). Once more, these financing effects are also innovation-specific. In the study by Mina *et al.* (2013), for example, a reduction in credit constraints does not emerge with respect to organizational innovations. On the contrary, these reduce the probability of getting financed (although for US firms only), possibly because of the negative signal associated with the entailed need for complex reorganization for the financing firm.

As the previous literature review reveals, innovation typology emerged as a relevant determinant of innovative SME credit rationing with respect to selected individual countries. In particular, the evidence on its unfolding changes when countries other than the United Kingdom are investigated, and this points to the possible influence of national financial regulations, institutions, and markets. More systematic cross-country evidence is therefore needed to ascertain whether different kinds of innovators face financial constraints to a different extent.

In addition to this empirical research gap, a potentially even more important gap remains to be filled with respect to the combination of innovation typologies in which firms can engage, rather than their specific nature. Different streams of research in innovation studies have actually shown that in addition to "single innovators" (of the four classical types we refer to above, i.e., product, process, organizational, and marketing),[2] there are firms that introduce—complementarily or even simultaneously—different types of innovation, attempting to benefit from the synergies of hybrid modes of learning and innovating (Jensen *et al.*, 2007). The simplest case of this is represented by what we could call "full technological innovators": firms that innovate across the board in the technological domain by introducing both product and process innovations but which keep their organizational and marketing structures unaltered. While the two kinds of technological innovations are generally treated as dichotomous and may reveal divergent firm strategies (e.g., quality-based vs. cost-based), recent studies have shown that they can be complementary or even super-modular, allowing firms to pursue superior business performance through their combination (Fonseca, 2014). A parallel case is represented by "full non-technological innovators": firms that "saturate" the spectrum of "soft" innovation activities by combining organization and marketing innovations, relying on their pre-existing technological base (in the absence of product and process innovations) (Schubert, 2010). On a higher combination level, we find what the literature has called "complex" innovators (Evangelista and Vezzani, 2010, 2012; Filippetti, 2011), referring to firms that have hands in both the technological and non-technological domains and combine the introduction of a new product and/or production process with that of a new organizational structure/procedure and/or marketing system/practice. The extent to which the two domains can be complementary is variable, spanning from the combination of one innovation typology per domain only (for example, product and marketing innovations or process and organizational innovations) to the combination of all four typologies ("super-complex innovators") and passing through a single cross-domain augmentation of the full technological profile (product and process plus organizational innovations, or plus marketing innovations) or of the full

2 For a standard definition of these four categories of innovation, see the benchmark reference represented by the OECD Oslo Manual (https://www.oecd.org/science/oslo-manual-2018-9789264304604-en.htm).

non-technological profile (organizational and marketing plus product innovations or process ones).

Do these innovation combinations affect the extent to which innovative SMEs experience credit rationing? In the absence of focal literature on the topic, we do not have strong a priori expectations or hypotheses, and we cannot do much more than be conjectural. On the one hand, it could be that "non-single" innovators appear riskier to lenders than single ones as they add uncertainty and agency costs across different projects, and such a perception could increase when the borrowing firm takes on the hazard of combining technological and non-technological innovations. On the other hand, it could be conversely argued that also being involved in a riskless kind of innovative activity (e.g., process innovation) could attenuate lenders' aversion to riskier innovations (e.g., product innovations) as it provides a sort of "quasi-guarantee" of returns. Following the same argument, a full technological/non-technological or even complex innovation profile—when contrasted to that of a single (or even occasional) one—could amplify the positive signaling effects to lenders that we mentioned above. In one way or another, even in the absence of strong predictions (as we will see in our empirical application), the diffusion of non-single innovators is so pervasive that their analysis is essential to evaluating credit supply to innovative SMEs.

2.2 Credit demand by (different kinds of) innovative SMEs

The type of data on which the majority of extant studies rely makes it very hard to distinguish between the demand for external finance and its supply (Mina *et al.*, 2013). This is quite unfortunate as a propensity differential between innovators and non-innovators in seeking bank credit could represent an additional source of the finance gap we are investigating.

From a theoretical point of view, the literature about the factors that could make the demand of external finance idiosyncratic for innovators is substantially thinner than that on credit supply and revolves around two contrasting hypotheses. On the one hand, by referring to the notable "pecking order theory" of finance (Myers and Majluf, 1984; Myers, 2000)[3] and applying it to the financing of innovative projects, it has been argued that innovative firms run out of internal funds more quickly than non-innovative ones and thus end up more in need of external financing, especially if they are of a small to medium size (Hall and Lerner, 2010). On the other hand, a recent theory about the existence of "discouraged borrowers" (Kon and Storey, 2003; Han *et al.*, 2009)[4] has prompted the argument that an innovation strategy could be among the conditioning factors of the relative model:[5] committing to such a strategy could increase the incidence of discouragement, and this would lead us to expect a reduced, rather than increased, credit demand by innovative vs. non-innovative firms (Freel *et al.*, 2012).

Unfortunately, the empirical evidence regarding these contrasting hypotheses is still scant and not yet decisive. What is more, to a larger extent than with respect to credit supply, the possible differentiating role of heterogeneous innovation typologies is only partially addressed. In the few studies that integrate the analysis of credit supply to innovative SMEs with a first econometric step regarding their demand for it, firm innovation usually turns out to be non-significant in accounting for the latter. This is the case of the study on UK and US SMEs by Mina *et al.* (2013), who find that neither R&D intensity (expenditures over assets) nor innovation outputs (product, process, and organizational) attenuate or aggravate their financial needs (both are not significant). Similarly, firm innovation does not appear to matter for the demand for external financing by Danish SMEs, according to a study by Hain and Christensen (2020). These authors find that such a demand is actually inelastic to both incremental and radical innovations. By considering the

3 According to this theory and unlike the Modigliani and Miller theorem (Modigliani and Miller, 1958; Miller and Modigliani, 1961) predicts, firms would not be indifferent between alternative sources of finance and instead start the financing of new (innovative) projects by resorting to internal cash flows. The search for external finance would occur only once internal funds have been exhausted, making external equity the least preferred option in the absence of proper collateral.

4 In brief, in the presence of "good" and "bad" (SME) borrowers, marked by heterogeneous costs of debt applications and with only an imperfect capacity of banks to screen them, even some "good" borrowers would refrain from applying due to a fear of being rejected.

5 Other factors include the magnitude of the banks' screening error, the size of the firms' application costs, the interest rate differential between banks and the moneylender, and the amount of available information.

types of introduced innovations in isolation,[6] both studies argue that innovation is not demanding enough to make internal funds insufficient for its financing. Combining these results with those of the negative effect of realized positive profits that they both find on the demand for external finance, the authors conclude by supporting the predictions of the pecking order theory. As Mina *et al.* (2013: 895–896) suggest, "the overwhelming majority of firms that did not seek external finance did not need any" (Cosh and Hughes, 2007; Fraser, 2009).

However, the fact that internal resources could actually be sufficient to make innovative firms refrain from changing their demand for external finance might be due to the kind of innovation considered or more accurately the kinds not considered. As mentioned above, previous studies do not (at least explicitly) address the role of non-single and complex innovators (see above), whose demand for credit could, however, be different from that of single ones. Once more, irrespective of the type of combined innovations, combination itself could put significant stress on the internal financial resources of firms. In general, non-single innovators are in fact pursuing changes that have more pervasive implications than the introduction of one single innovation and which, accordingly, involve costs over and above those of the relative innovation inputs (e.g., R&D and other intangible and tangible investments). To give an example, the combination of product and process innovations could make firms incur costs for adapting or even reconfiguring the production process and the value chain, costs that are greater than those incurred for implementing only one of the two typologies. Of course, the specific type of combination could make the difference. The typical "bundling" of product and marketing innovations (Lewandowska and Gołębiowski, 2012) or of process and organizational innovations (Alänge and Steiber, 2011), for example, could enable firms to benefit from economies of scale in the costs of innovating and make the pecking order theory hold even in the presence of non-single innovators. In contrast, "super-complex innovators" (innovating in terms of product, process, organization, and marketing) might find the need to switch to external financing more urgent. In one way or another, the typologies of innovation combination on which we focus in this paper also appear to be important in the analysis of credit demand.

Innovation typologies and combinations are also relevant with respect to the other theoretical argument about credit demand that we have referred to: the discouraged borrower effect. In the few empirical studies that have attempted to test it, the focus is simply on whether innovation makes firms afraid to demand external credit—and results are once more contradictory. With respect to a sample of small UK firms in 2005, Freel *et al.* (2012) do not find confirmation of an expected correlation between credit discouragement and an innovation variable captured as part of the firms' competitive strength. On the contrary, supportive evidence emerges from a study by Lee and Brown (2016) of UK firms at the regional level: innovative firms in peripheral regions are more likely to be discouraged from applying for bank finance than both non-innovative firms in the same regions and innovative firms elsewhere.

In searching for more consistent empirical evidence about the discouraged borrower hypothesis, it seems to us that the explicit consideration of non-single or even complex innovators would allow us to better capture the underlying mechanisms. In particular, we might expect that firms anticipate and discount that lenders may be less capable of screening debt applications from more complex innovators as these span multiple innovation domains (see Section 2.1 the previous section). By incorporating this expectation into the cost function of their debt applications, they may thus refrain from applying in the fear of being rejected, possibly to a greater extent than single innovators. Once more, the effect could be different for different kinds of innovation combinations, in a way that we find hard to predict in the absence of focal literature. Still, following our previous arguments, we expect that the discouraged borrower effect would be greater for complex innovators than for non-complex (and single) innovators.

As we have repeatedly mentioned, possibly more than with respect to credit supply, wider and more systematic empirical evidence is required to ascertain the role of innovation and innovation

6 As is standard with the use of innovation surveys, such as the Community Innovation Survey, respondent firms are asked to state whether they have introduced a certain type of innovation (e.g., product or process), which then enters in the estimates as a dummy, irrespective of the introduction of other types of innovation, which are at most controlled for.

typologies/combinations in credit demand, as the existing evidence is nearly exclusively related to the United Kingdom. As we will see in Section 3, our empirical application makes use of survey data (SAFE) that covers a large set of countries and the collection of which involved detailed questions about SME innovation, credit supply, and credit demand. In particular, the set of items the survey offers to respondents when asking about their credit demand includes both the availability of internal funds and the fear of being turned down, thus allowing us to undertake a closer inspection of the theoretical arguments reviewed above.

3. Empirical analysis

Our empirical investigation is based on data from SAFE, a semi-annual survey of European SMEs administered by the European Commission and the European Central Bank.[7] Starting from 2009, each 6-monthly wave of the survey has been administered to a randomly selected sample of non-financial SMEs in the Dun & Bradstreet business register operating in the manufacturing, mining and utilities, construction, and trade and services sectors.

Using the 11th to the 21st SAFE waves, covering the 6-year period from April 2014 to November 2019, we combine information on the experiences of SMEs in accessing finance (demand and supply) with qualitative but disaggregated information about their innovation status and a suitable set of controls. The SAFE data actually cover a large spectrum of homogeneous and harmonized firm-level data for all European countries, which allows us to minimize the usual problems of non-observed heterogeneity. Nonetheless, in order to reduce confounding effects due to the idiosyncratic financial markets of peripheral countries, our analysis refers to SMEs belonging to 11 countries of the EU15—i.e., the EU prior to the accession of May 1, 2014—for which data are available for the full set of variables over the 2014–2019 period. These 11 countries are Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, and Spain.

As the firms included in the survey are randomly selected in each of the considered waves (11th–21st), the dataset obtained by combining them for the EU15 is a non-balanced panel of 36,699 firm-level observations. In order to attenuate problems of reverse causality in our estimates, however, we use a lagged value of our focal innovation variables, and this forces us to drop four countries, resulting in a smaller panel of 15,020 firms present in consecutive waves for the abovementioned 11 countries over the 2014–2019 period. While this entails an observation loss of more than 50% of the initial firms, we deem it a necessary price to pay for increasing the reliability of our estimates.[8]

3.1 Variables and econometric strategy

Following previous studies (Mina *et al.*, 2013; Hain and Christensen, 2020), we unfold our econometric strategy in two steps, referring to (bank) credit demand and supply, respectively.

3.1.1 Credit demand

We start our analysis of SME credit demand by looking at their propensity to seek bank loans, using as dependent variable a dummy, $Credit\_Demand_i$, taking a value of 1 if firm i has applied for a loan over the previous 6 months and 0 otherwise (question Q7A_a of the SAFE). It should be noted that this variable captures a generic demand for credit expressed by the focal firm i and does not refer to a financial need specifically linked with the realization of an innovation project.[9] Thus, we investigate whether the innovation status of firms has implications for their financial operations across the board (i.e., entering a new market rather than acquiring new participations)

7 Information on SAFE is available at https://www.ecb.europa.eu/stats/ecb_surveys/safe/html/index.en.html.

8 In spite of the strong drop in the number of observations, when comparing the two samples (the full one of 36,699 observations and the reduced one we use in our analysis), it emerges that the standard statistics of all variables are not dissimilar across them. Comparative descriptive statistics are available from the authors upon request.

9 While question Q7A_d of SAFE also refers to other forms of bank financing to firms (e.g., credit line, bank overdraft, or credit card overdraft), we focus on bank loans only as these typically cover the kind of investment expenses that generally drive innovation projects, while the former are instead more commonly used for current expenses.

and whether the same status has risk and signaling implications that could make a difference to the lender also for credit needs not strictly related to an innovation project.

We run the following panel logit regression:

$$P(Credit\_Demand_i = 1 | X_i, Z_i) = \Lambda(\beta_i X_i + \delta Z_i), \tag{1}$$

where $\Lambda(Z) = e^z/(1+e^z)$ is the logistic function, X_i is a vector of explanatory variables, including those related to innovation, and Z_i indicates a series of firm-specific control variables.

As far as the explanatory variables are concerned, X_i comprises the qualitative variables through which SAFE allows us to assess a firm's corporate finance: $Profit\_change_I$, with categorical values of 1 if profit decreased, 2 if it remained stable, and 3 if it increased during the time of each wave; $Leverage\_down_i$, equal to 1 if the debt/assets ratio of firm *i* decreased in the same period and 0 otherwise; $Public\_finance_i$, a categorical variable ranging from 1 to 3 and indicating a decrease (1), an unchanged status (2), or an increase (3) in the access to public financial support (including guarantees) during the time of each wave.[10] The financial status of the firms is integrated with two other dummies: $Single/family\_owner_i$, referring to firms that are individually or family-owned, and $Independent_i$, capturing firms that are not part of business groups. Although for different reasons, pertaining to the difficulties in accessing the capital market (the former two) and the lack of intra-group capital financing (the third), these kinds of SMEs are expected to be more reliant on bank loans than their counterparts (Mina *et al.*, 2013).

The vector Z_i includes a set of non-financial structural controls for the observed firms. First of all, we consider the following three structural features of the focal firms: Age_i, assuming progressively higher categorical values for increasingly older firms (1: younger than 2 years; 2: between 2 and 4 years; 3: between 5 and 9 years; 4: 10 years old and over); $Size_i$, denoting increasingly larger SMEs (1: micro-firms of between 1 and 9 employees; 2: small firms with between 10 and 49 employees; 3: medium-sized firms with between 50 and 249 employees); and $Export_i$, measuring four classes (1–4) of firm total turnover accounted for by exports (1: nil; 2: below 25%; 3: between 25% and 50%; and 4: more than 50%). Secondly, we also try to control for the financial "health" of the focal firms with the following variables: $Exper\_growth_i$, which ranges from 1 to 3 and identifies the sample firms that declared having experienced a decrease in their specific outlook (with respect to sales, profitability, or their business plan) during the time of each wave (1), an unchanged status (2), or an increase (3); $Expect\_growth_i$, which ranges from 1 to 4 and refers an expected turnover growth over the next two to three years that is negative (1), nil (2), moderate (i.e., below 20%) (3), or substantial (i.e., over 20%) (4). Finally, sector ($Manufacturing\_etal_i$, $Construction_i$, $Trade_i$, and $Services_i$), country (our 11 EU ones), and temporal fixed effects in the form of 10 separate dummies to capture the 11 periods in our temporal window are inserted as well.[11]

In order to address our focal research questions, we augment the previous explanatory variables with a set of innovation variables. To start with, we define a generic innovation dummy, $Inno_i$, which takes a value of 1 if the focal firm is innovative across the board (and 0 otherwise), meaning it has introduced at least one (and possibly more) of the four innovation typologies (and combinations) that the SAFE survey allows us to consider: product, process, organizational, and marketing innovations. While it neglects the specific nature of innovative SMEs, this is an important variable that serves to distinguish the extent to which they differ from non-innovative ones in terms of credit supply and demand. We then look at the profiles firms construct with respect to their innovation activities, and *instead of* using the dummy $Inno_i$, we distinguish innovative SMEs according to their being involved in technological innovations (i.e., product

10 As argued in Section 2, this could affect the demand for credit both directly, in a substitutive way, as supported firms might need less financing, and indirectly as the received public support could provide lenders with the assurance of their financial reliability.

11 With respect to the sector dimension of survey firms, unfortunately SAFE releases information only at 1 NACE digit. Accordingly, in our estimates, we can do nothing but include sector dummies for manufacturing, mining and utilities, construction, and trade and services, which are equal to 1 if the focal firm belongs to the manufacturing, mining and utilities, construction, trade and services sectors, respectively, and 0 otherwise. Services is the controlling group for sector effects.

and process innovations)—*Inno_Tech*$_i$—rather than non-technological ones only (i.e., organizational and marketing innovations)—*Inno_NTech*$_i$—and contrasting them with non-innovative SMEs (as a benchmark). More precisely, *Inno_Tech*$_i$ is a dummy variable taking a value of 1 if firm *i* has introduced a product and/or process innovation, irrespective of whether it has done so in the non-technological domain, while *Inno_NTech*$_i$ takes a value of 1 if the focal firm has introduced an organizational and/or a marketing innovation only, in the absence of technological ones.[12]

We finally move to a more fine-grained analysis of innovation typologies and substitute the previous two dummies—*Inno_Tech*$_i$ and *Inno_NTech*$_i$—with as many as 15 dummies, through which we univocally distribute our sample firms among 15 distinct innovation profiles. These profiles can be obtained by combining the four basic typologies and contrasting them with the benchmark case of a fully non-innovative profile, that is, of no innovation of any kind. The first four profiles refer to what we call "single innovators" and are accounted for by four dummies that take a value of 1 if the firm has introduced a certain innovation typology in an *exclusive manner* and 0 otherwise: *Inno_Pd*$_i$, *Inno_Pc*$_i$, *Inno_Or*$_i$, and *Inno_Mk*$_i$.[13] We then have the full technological and full non-technological innovation profiles, captured by a dummy that takes a value of 1 if the firm has introduced both product and process innovations, *Inno_Pd_Pc*$_i$, or both organizational and marketing innovations, *Inno_Or_Mk*$_i$, respectively, and 0 otherwise. Finally, we consider as many as nine types of "complex innovators," for which we build up the following variables: 4 twofold dummies, *Inno_Pd_Mk*$_i$, *Inno_Pd_Or*$_i$, *Inno_Pc_Mk*$_i$, and *Inno_Pc_Or*$_i$, taking a value of 1 if one of the two technological variants (product or process innovation) combines with one of the two non-technological variants (organizational or marketing innovation) and 0 otherwise; 4 threefold dummies, *Inno_Pd_Pc_Or*$_i$, *Inno_Pd_Pc_Mk*$_i$, *Inno_Pd_Or_Mk*$_i$, and *Inno_Pc_Or_Mk*$_i$, taking a value of 1 if one of the two pairs of technological (product and process innovation) and non-technological (organizational and marketing innovation) variants combine with one of the two non-technological (organizational or marketing innovation) and technological (product or process innovation) variants, respectively (and 0 otherwise); and 1 fourfold dummy, *Inno_Pd_Pc_Or_Mk*$_i$, taking a value of 1 if the firm has introduced all four typologies of innovation and 0 otherwise.

Still with respect to innovation, in a robustness check of our results, we build up two additional sets of variables. A first set is intended to capture the extent to which the role of *complexity* in innovating (resulting from combining innovation typologies of different kinds) is inherently due to the *intensity* of innovation activities, as could be simply reflected by the number of innovation typologies implemented. In order to do this, we consider as focal regressors to disaggregate the sample of innovative SMEs (and contrast these with non-innovative ones) four dummies that tell us whether the focal firm has introduced one (*Inno1*$_i$), two (*Inno2*$_i$), three (*Inno3*$_i$), or four (*Inno4*$_i$) types of innovation of any kind, not taking into account the nature of the innovations that are combined.[14] The second innovation variable for which we run a robustness check is a simple ordinal variable, which for each and every firm *i* counts the number of innovation typologies that it has introduced: *InnoCount*$_i$ (=0, 1, 2, 3, and 4). In addition to providing us with further insights about the role of innovation intensity vs. complexity, this variable enables

12 Strictly speaking, the former (*Inno_Tech*) could involve more than "simply" technological innovators if firms have also introduced organizational and/or marketing innovations, but they are distinguished from the latter (*Inno_NTech*) by a technological imprinting that is, by construction, exclusive to them.

13 The four types of innovation are identified by question Q1 of SAFE, which asks whether the responding firm has in the previous 12 months undertaken: "(1) a new or significantly improved product or service to the market; (2) a new or significantly improved production process or method; (3) a new organization of management; (4) a new way of selling your goods or services." Unlike the other variables in the survey, question Q1 refers to the previous 12 months and is thus provided by SAFE every two waves. In order to restore this information at the 6-month wave level, we have replicated this information only for those firms that are present in consecutive waves. In so doing, we assume that if a firm has declared to have undertaken innovation during the last 12 months, this information holds true for the entire period and thus covers two waves. In addition to that, let us remember that among the zeros of the corresponding single-innovator dummies (say, *Inno_Pd*$_i$), we can find both non-innovative firms and firms that introduced another type of innovation (different from *Inno_Pd*$_i$) or combined the focal innovator type (*Inno_Pd*$_i$) with some other. By construction, the union of the 15 innovation categories gives non-innovators as a complement.

14 Of course, the last dummy (*Inno4i*) corresponds to that which we have termed *Inno_Pd_Pc_Or_Mk*$_i$.

us to test whether the role of innovation in external financing could be non-linear, by considering its squared term.

As an additional added value with respect to the extant literature, we also look at the motivations for SME credit demand by building up a four-item categorical version of the dependent variable *Credit_Demand_Mot*$_i$ (y), which codes the following SME outcomes with respect to bank loan applications over the previous 6 months (question Q7A_a of SAFE): (1) applied (y_1); (2) did not apply because of fear of rejection (y_2); (3) did not apply because of sufficient internal funds (y_3); (4) did not apply for other reasons (y_4).

Faced with a qualitative dependent variable with more than two discrete, non-naturally ordered outcomes, we re-run equation (1) with a panel multinomial logit regression. In particular, using the outcome of an successful credit application as a baseline (y_1), we investigate whether the innovative status of firms affects their probability of refraining from applying because of a "discouraged borrower" effect (y_2); sufficient internal funds (y_3), as in the pecking order theory; or other reasons (y_4).[15] Descriptive statistics of these variables are reported in Table 1.

3.1.2 Credit supply

As for the supply of credit that SMEs eventually receive (or not), we investigate this by using two dependent variables. First of all, we define a dummy, *Credit_Constraint*$_i$, that takes a value of 1 if the focal firm has been credit-constrained—either because it was refused its loan application by the bank or because it refused it itself as too costly—and 0 otherwise (question Q7B_a of SAFE).[16] Secondly, we investigate the role of innovation and innovation typologies/combinations in accounting for the amount by which financial rationing occurs by using a categorical dependent variable, *Credit_Received_Amnt*$_i$ (y), referring to the cases in which the applicant firms (1) received the requested credit only partially (y_2), (2) received it in full (y_3), or (3) were credit-constrained (y_1), with the latter being the benchmark case. In order to build this categorical variable, we used the information provided in question Q7B_a of SAFE.

Symmetrically to our analysis of the demand side, for the supply side, we start by estimating the following model:

$$P(Credit\_Constraint_i = 1|X_i, Z_i) = \Lambda(\beta_i X_i + \delta Z_i), \tag{2}$$

where X_i and Z_i are vectors that capture the same sets of explanatory variables and firm-specific control variables as in equation (1), respectively.

As in the case of credit demand, note that the supply of credit we refer to is not necessarily linked to the realization of an innovation project by the focal firm, but rather to the bank credit that innovative vs. non-innovative firms have received in response to their generic financial needs.

As the only firms reporting credit obtained by banks (or not) are those having requested it, a problem of selection bias can of course emerge. In order to deal with this, we estimate a panel probit model with sample selection. In the selection equation, *Credit_Demand*$_i$ is estimated against the set of regressors and controls of equation (1), including those referring to firm innovation status. These variables are then jointly used in the output equation as explanatory variables of *Credit_Constraint*$_i$, with the exception of an exclusion restriction. In particular, we follow Mina *et al.* (2013) in using information about the independent status of the firm as a restriction variable. In doing so, we assume that a firm belonging to a group can potentially access finance from its parent company and/or group partners and would thus be less likely to request a bank loan. Conversely, there is no reason to believe that being independent should affect the chances of having the credit request turned down or accepted by the bank.

A similar procedure to account for sample selection is adopted to estimate *Credit_Received_Amnt*$_i$. More specifically, setting the credit constraint outcome (y_1) as the baseline, we run a multinomial probit with selection bias and look at the role of innovation in affecting

15 As for the last outcome, it is a residual one that includes all motivations for refraining from applying for a bank loan other than y_2 *and* y_3. Although SAFE does not provide information on this outcome, we can infer that it might also refer to the use of informal finance (i.e., family, friends, and networks).

16 In both cases, the credit supply at stake does not unfold and the firm remains credit-constrained.

Table 1. Descriptive statistics

Variables	Obs	Mean	Std. dev.	Min	Max
Credit_Demand	15,020	0.335	0.472	0	1
Credit_Demand_Mot:	15,020	2.452	1.141	1	4
Applied (y_1)	15,020	0.335	0.472	0	1
Did not apply for fear of rejection (y_2)	15,020	0.069	0.254	0	1
Did not apply because of sufficient internal funds (y_3)	15,020	0.404	0.491	0	1
Did not apply for other reasons (y_4)	15,020	0.192	0.394	0	1
Credit_Constraint	4,115	0.082	0.275	0	1
Credit_Received_Amnt:	4,115	1.700	0.613	1	3
Loan rejected or refused (y1)	4,115	0.082	0.274	0	1
Loan partially received (y2)	4,115	0.139	0.346	0	1
Loan fully received (y3)	4,115	0.779	0.415	0	1
Inno	12,389	0.625	0.484	0	1
Inno_Tech	12,389	0.445	0.497	0	1
Inno_NTech	12,389	0.179	0.384	0	1
InnoCount	12,389	1.227	1.220	1	4
Inno1	12,389	0.249	0.432	0	1
Inno2	12,389	0.205	0.403	0	1
Inno3	12,389	0.116	0.321	0	1
Inno4	12,389	0.055	0.228	0	1
Inno_Pd	12,389	0.072	0.258	0	1
Inno_Pc	12,389	0.045	0.206	0	1
Inno_Or	12,389	0.093	0.290	0	1
Inno_Mk	12,389	0.040	0.197	0	1
Inno_Pd_Pc	12,389	0.055	0.229	0	1
Inno_Pd_Or	12,389	0.031	0.174	0	1
Inno_Pd_Mk	12,389	0.033	0.179	0	1
Inno_Pc_Or	12,389	0.030	0.171	0	1
Inno_Pc_Mk	12,389	0.008	0.089	0	1
Inno_Or_Mk	12,389	0.047	0.211	0	1
Inno_Pd_Pc_Or	12,389	0.040	0.196	0	1
Inno_Pd_Pc_Mk	12,389	0.029	0.167	0	1
Inno_Pd_Or_Mk	12,389	0.028	0.164	0	1
Inno_Pc_Or_Mk	12,389	0.020	0.139	0	1
Inno_Pd_Pc_Or_Mk	12,389	0.055	0.228	0	1
Profit_change	15,020	2.018	0.796	1	3
Leverage_down	15,020	0.293	0.455	0	1
Public_finance	15,020	1.911	0.543	1	3
Single/family_owner	15,020	0.852	0.355	0	1
Independent	15,020	0.901	0.298	0	1
Age	15,020	3.816	0.518	1	4
Size	15,020	1.953	0.808	1	3
Export	14,950	1.889	1.059	1	4
Exper_growth	15,020	2.198	0.712	1	3
Expect_ growth	12,325	2.720	0.713	1	4
Manufacturing_etal	15,020	0.301	0.459	0	1
Construction	15,020	0.103	0.304	0	1
Trade	15,020	0.247	0.431	0	1
Wave 12	15,020	0.111	0.314	0	1
Wave 13	15,020	0.116	0.320	0	1
Wave 14	15,020	0.106	0.308	0	1
Wave 15	15,020	0.101	0.302	0	1
Wave 16	15,020	0.108	0.311	0	1

(continued)

Table 1. (Continued)

Variables	Obs	Mean	Std. dev.	Min	Max
Wave 17	15,020	0.103	0.304	0	1
Wave 18	15,020	0.090	0.286	0	1
Wave 19	15,020	0.087	0.282	0	1
Wave 20	15,020	0.087	0.282	0	1
Wave 21	15,020	0.091	0.287	0	1

Our elaboration of SAFE data using the 11th to 21st waves.
Credit_Demand_Mot is a categorical variable that codes (from 1 to 4) the occurrence of a bank loan application by SMEs and the motivations for their refraining from applying over the previous 6 months: y_1, y_2, y_3, y_4.
Credit_Received_Amnt is a categorical variable that codes (from 1 to 3) the experience of a loan refusal by the applicant SMEs and the extent to which the loan has been accepted: y_1, y_2, y_3.

the extent to which SMEs manage to overcome their eventual credit constraint by getting their loan request partially (y_2) or totally accepted (y_3).

The descriptive statistics of the variables employed in the analysis are reported in Table 1. The correlation matrix displaying pairwise correlations is instead available in the Appendix (Table A1).

Before turning to the results, it is important to stress that while using lagged values of our focal innovation variables can mitigate some concerns regarding reverse causality, it does not completely eliminate other possible sources of endogeneity such as unobserved firm characteristics (different from those we have already controlled for) that can cause both credit demand/supply and innovation, without the latter being causally linked to the former. R&D investments, for example, could both contribute to firm innovation and lead firms to seek finance but to expand into new markets as a result of a successful innovation. In the presence of such an econometric issue, our results should be read in terms of correlations and associations that only hint at causal relationships.

4. Results

4.1 Credit demand

4.1.1 Panel logit model

Starting with the analysis of SME demand for bank credit, Table 2 presents the average marginal effects (AMEs) of the regressors for the panel logit model of equation (1), accounting for firm *i* seeking bank credit in three specifications.[17] The first (column 2.a) considers the innovative status of the sample firms in generic terms; the second (column 2.b) distinguishes innovative firms from non-innovative ones by considering the technological vs. non-technological nature of their innovation; the third (column 2.c) distinguishes the 15 innovative profiles we have isolated with respect to the benchmark case of non-innovative firms.

Before focusing on these innovation variables, note that in all specifications the majority of the other predictors of credit demand and of the controls are significant and display the expected sign.[18] An improvement in SME profits (*Profit_change*) correlates negatively with their probability of seeking external finance, consistent with a pecking-order kind of argument (see Section 2). Still in line with financial arguments, when liabilities with respect to assets get smaller (*Leverage_down*) and the leverage decreases, the probability that SMEs apply for a bank loan also decreases. Finally, a positive change in the access to public financial support and guarantees (*Public_finance*) is associated with SMEs being more reluctant to seek external credit, possibly because of this other support attenuating their financial needs. As expected, single-owned and/or family businesses correlate with a higher probability of requesting credit, and the same holds true for independent firms not relying on business-group financing. The propensity to resort to

17 Coefficients are available from the authors upon request.
18 As the innovation variables of the three specifications actually provide the same kind of information for the sample firms, although in a different (compact and disaggregated, respectively) format, the marginal effects of the controls are—as expected—coincident or nearly so.

Table 2. Seeking bank credit panel logit model (lagged regressors, $t-1$), average marginal effects

	(2.a)	(2.b)	(2.c)
Inno	0.046***		
	(0.010)		
Inno_Tech		0.057***	
		(0.010)	
Inno_NTech		0.021	
		(0.013)	
Inno_Pd			0.029
			(0.018)
Inno_Pc			0.031
			(0.023)
Inno_Or			0.011
			(0.017)
Inno_Mk			0.060***
			(0.023)
Inno_Pd_Pc			0.059***
			(0.020)
Inno_Pd_Or			0.074***
			(0.025)
Inno_Pd_Mk			0.019
			(0.027)
Inno_Pc_Or			0.089***
			(0.026)
Inno_Pc_Mk			0.032
			(0.048)
Inno_Or_Mk			0.007
			(0.022)
Inno_Pd_Pc_Or			0.061***
			(0.023)
Inno_Pd_Pc_Mk			0.051**
			(0.026)
Inno_Pd_Or_Mk			0.074***
			(0.026)
Inno_Pc_Or_Mk			0.090***
			(0.031)
Inno_Pd_Pc_Or_Mk			0.087***
			(0.020)
Profit_change	−0.013**	−0.013**	−0.013**
	(0.006)	(0.006)	(0.006)
Leverage_down	−0.093***	−0.093***	−0.092***
	(0.010)	(0.010)	(0.010)
Public_finance	−0.016*	−0.015*	−0.015*
	(0.009)	(0.009)	(0.009)
Single/family_owner	0.042***	0.042***	0.042***
	(0.015)	(0.015)	(0.015)
Independent	0.068***	0.068***	0.067***
	(0.019)	(0.019)	(0.019)
Age	0.023**	0.023**	0.023**
	(0.009)	(0.009)	(0.009)
Size	0.106***	0.107***	0.107***
	(0.007)	(0.007)	(0.007)
Export	0.009*	0.008	0.008
	(0.005)	(0.005)	(0.005)
Exper_growth	0.032***	0.031***	0.031***
	(0.007)	(0.007)	(0.007)
Expect_ growth	0.017**	0.017**	0.015**
	(0.007)	(0.007)	(0.007)

(continued)

Table 2. (Continued)

	(2.a)	(2.b)	(2.c)
Manufacturing_etal	0.042***	0.040***	0.041***
	(0.013)	(0.013)	(0.013)
Construction	0.028*	0.030*	0.030*
	(0.017)	(0.017)	(0.017)
Trade	0.040***	0.040***	0.041***
	(0.013)	(0.013)	(0.013)
Time effects	Yes	Yes	Yes
Country effects	Yes	Yes	Yes
Observations	15,020	15,020	15,020
Log-likelihood	−8749.9	−8745.7	−8736.6
Wald test	677.9	684.5	699.5
P-value	0.00	0.00	0.00
McFadden	0.05	0.06	0.06
Nagelkerke	0.08	0.08	0.08
Akaike	17,570	17,563	17,571
Schwarz	17,836	17,838	17,944

Table 2 shows the AMEs obtained from the three specifications (2.a, 2.b, 2.c) of the panel logit model of equation (1), whose dependent variable is the dummy $Credit\_Demand_i$, taking a value of 1 if SMEs demand credit and 0 otherwise. Standard errors are in parentheses. Goodness-of-fit measures refer to the panel logit model (with coefficients).
Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

bank credit grows with SME size and—albeit only slightly significantly—with their export internationalization, which is consistent with previous evidence (Mina *et al.*, 2013), while older SMEs are apparently more credit-seeking. SMEs that perceive themselves to be in a phase of current or prospected growth also appear more likely to seek bank credit, possibly in order to pursue their potential growth perspectives. As for the sector dummies, the results show that belonging to the manufacturing (and mining and utilities) or trade sectors, compared to services (the control group), correlates with a higher probability of requesting bank loans.

Coming to our focal regressors, specification (2.a) shows that generic innovative SMEs have a nearly 5% (0.46) higher probability of applying for a bank loan than non-innovative ones, on average. This result is highly significant and contrasts previous inconclusive evidence about innovation and credit demand by SMEs in the United Kingdom, the United States (Mina *et al.*, 2013), and Denmark (Hain and Christensen, 2020). With respect to a wider set of countries, an innovative status seems to aggravate the external financial needs of European SMEs across the board. This suggests an additional policy issue to that of integrating and/or supplementing the insufficiency/lack of internal resources that SMEs can use for innovation, which we discuss later.

Moving to column (2.b), the higher propensity to request credit shown by generic innovative SMEs finds novel interesting qualifications when their specific innovative profile is considered. To start with, whether firms' innovations have a technological base or not makes a difference. Indeed, it is only with the presence of technological innovations (of some kind) (*Inno_Tech*) that the demand for credit increases with respect to that of non-innovative firms. Conversely, when firms innovate in domains other than those related to new product development and new process design (*Inno_NTech*), in a so-called "soft" way (organizational or/and marketing), their credit demand does not change with respect to the benchmark.

Additional nuances emerge from Model (2.c), where we look at the specific innovation profiles that are hidden behind the previous two innovation variables. At the outset, let us note that only one of the four single-innovator profiles reveals a significantly positive coefficient and that the same occurs for just three out of the six double-innovator profiles. The propensity to request bank credit is significantly higher (than the benchmark) for all of the threefold innovative profiles that we consider and for the full-spectrum or "super-complex" innovators. Pulled together, these results suggest that the external financial needs of SMEs increase also and above all with the extent of their involvement in the different domains of the innovative process. Indeed, with the exception of (single) marketing innovators, innovating in one domain only does not make a difference in terms of requested external finance. The case of marketing innovators is unique and may be explained by the fact that SMEs typically lack formal marketing departments and the internal resources these could make available to the development of new marketing practices. Combining or simply adding[19] two types of innovation apparently exacerbates firms' financial needs but not in general. A significantly marginal effect is only revealed by full technological innovators (*Inno_Pd_Pc*) and by technological innovators that integrate one of the relative typologies (product or process innovation) with an organizational kind of innovation in the non-technological domain (*Inno_Pd_Or* and *Inno_Pc_Or*). Quite interestingly, on the first rung of the innovation complexity ladder (twofold innovation), the introduction of technological (product or process) changes appears necessary to activate a significant and positive correlation with credit demand and equally necessary for that to happen is the concomitant occurrence of a novel organizational change. Considering that technological innovations are typically coupled with organizational ones by firms that pursue a structural/systemic kind of change,[20] this result suggests that—as expected—the demand for bank credit is higher for SMEs that innovate in a "transformative" way. On the higher rungs (threefold and fourfold) of the innovation complexity ladder, however, the extra need (with respect to the benchmark) for external finance gets general, for example, by applying also to full non-technological innovators that innovate in one of the technological domains. Finally, in further confirming our argument about the importance of the firms' innovation typologies, the full-innovator profile (*Inno_Pd_Pc_Or_Mk*) shows one of the highest marginal effects: when SMEs have this "super-complex" innovative profile, their propensity to request bank credit increases by as many as 9 percentage points with respect to non-innovative SMEs.

4.1.2 Panel multinomial logit model

Further insights about SME credit demand emerge by looking at the results of the panel multinomial logit estimation of equation (1) with respect to the relative motivations. Applying (y_1) as a benchmark case for *Credit_Demand_Mot*$_i$ (y), Table 3 shows the Average Marginal Effect (AME) that a dichotomic change in our focal innovation predictors has on the different motivations for not applying for credit that SAFE data enables us to consider.[21] These are: fear of rejection (y_2), available internal funds (y_3), and other reasons (y_4), reported in columns 3.a, 3.b, and 3.c, respectively.

Starting with panel A, which considers the innovation status of the focal firms in generic terms (*Inno*), note that this innovator status does not significantly correlate with the probability of being a discouraged borrower for fear of rejection, compared to the non-innovator status (column 3.a). Contrasting previous evidence about the greater financial discouragement shown by innovators at the regional level for the United Kingdom (Lee and Brown, 2016), this effect does not seem to emerge across the wide set of countries that we consider here. The substantial absence of a discouraged borrower effect among innovative firms is confirmed by the estimates of panel B, where we start unpacking the innovative status of SMEs into technological and non-technological: both variables (*Inno_Tech* and *Inno_NTech*) are in fact not significant in column 3.a. A similar result emerges when considering the 15 innovative profiles of panel C. While full (and exclusive) non-technological innovators (combining organizational and marketing innovations only) show a significantly higher chance of refraining from applying because of a fear of rejection—possibly because of the complex outcome of such an intangible innovation profile in the banks' eyes—the AME is quite low (about 2.1%), and in the case of a fourfold type of innovator, the AME (of about 1.5%) is only significant at the 10% level.

19 Unfortunately, we cannot know whether innovations were combined on purpose or whether they simply occurred in the same period but disjointedly.

20 The case of systemic architectural innovations, which combine innovations in the way product and organizational modules are combined, represents an example of this (Colfer and Baldwin, 2016).

21 The AMEs on the benchmark case of applying are available from the authors upon request, and, apart from small differences due to rounding and the adopted algorithms, they are of course consistent with the results of Table 2. In interpreting the AMEs of Table 3, it should be recalled that they are calculated by retaining the probability-weighted average of all the coefficients in equation (1) (see (15.19) in Cameron and Trivedi, 2005).

Table 3. Not seeking bank credit by motivation: panel multinomial logit (lagged regressors, $t-1$), average marginal effects

	(3.a) Fear of rejection (y_2)	(3.b) Available internal funds (y_3)	(3.c) Other reasons (y_4)
Panel A			
Inno	0.004	−0.056***	0.003
	(0.004)	(0.010)	(0.008)
Profit_change	−0.020***	0.051***	−0.016***
	(0.003)	(0.007)	(0.005)
Leverage_down	−0.014***	0.115***	−0.007
	(0.005)	(0.011)	(0.008)
Public_finance	−0.047***	0.065***	0.006
	(0.004)	(0.009)	(0.007)
Single/family_owner	0.007	−0.063***	0.014
	(0.007)	(0.016)	(0.012)
Independent	−0.001	−0.031	−0.041***
	(0.008)	(0.019)	(0.014)
Age	−0.011***	0.001	−0.010
	(0.003)	(0.010)	(0.007)
Size	−0.016***	−0.032***	−0.051***
	(0.003)	(0.007)	(0.005)
Export	−0.003	−0.001	−0.006
	(0.002)	(0.005)	(0.004)
Exper_growth	−0.001	−0.004	−0.022***
	(0.003)	(0.008)	(0.006)
Expect_ growth	0.002	−0.005	−0.011**
	(0.003)	(0.007)	(0.005)
Manufacturing_etal	0.014**	−0.036**	−0.025**
	(0.005)	(0.014)	(0.010)
Construction	0.018***	−0.025	−0.024*
	(0.007)	(0.018)	(0.013)
Trade	−0.000	−0.002	−0.040***
	(0.005)	(0.014)	(0.010)
Time effects	Yes	Yes	Yes
Country effects	Yes	Yes	Yes
Observations	15,020		
Log-likelihood	−16,846.6		
Wald	1998.6		
P-value	0		
McFadden	0.09		
Nagelkerke	0.22		
Akaike	33,903		
Schwarz	34,703		
Panel B			
Inno_Tech	0.003	−0.062***	−0.002
	(0.004)	(0.011)	(0.008)
Inno_NTech	0.008	−0.047***	0.015
	(0.006)	(0.014)	(0.011)
Observations	15,020		
Log-likelihood	−16,841.5		
Wald	1975.6		
P-value	0.00		
McFadden	0.09		
Nagelkerke	0.22		
Akaike	33,899		
Schwarz	34,722		
Panel C			
Inno_Pd	−0.000	−0.017	−0.015
	(0.008)	(0.020)	(0.015)

(Continued)

Table 3. (Continued)

Inno_Pc	−0.006	−0.021	−0.003
	(0.012)	(0.025)	(0.019)
Inno_Or	0.009	−0.052***	0.029**
	(0.007)	(0.018)	(0.013)
Inno_Mk	−0.013	−0.038	−0.002
	(0.010)	(0.024)	(0.018)
Inno_Pd_Pc	−0.011	−0.045**	−0.010
	(0.010)	(0.022)	(0.017)
Inno_Pd_Or	0.006	−0.079***	−0.011
	(0.011)	(0.030)	(0.023)
Inno_Pd_Mk	0.009	−0.033	0.004
	(0.010)	(0.028)	(0.021)
Inno_Pc_Or	0.006	−0.080***	−0.021
	(0.012)	(0.029)	(0.023)
Inno_Pc_Mk	−0.020	−0.101**	0.085**
	(0.023)	(0.050)	(0.033)
Inno_Or_Mk	0.021**	−0.046*	0.003
	(0.008)	(0.023)	(0.017)
Inno_Pd_Pc_Or	0.006	−0.046*	−0.028
	(0.010)	(0.026)	(0.021)
Inno_Pd_Pc_Mk	0.017	−0.077***	0.002
	(0.010)	(0.028)	(0.021)
Inno_Pd_Or_Mk	−0.006	−0.075***	0.012
	(0.011)	(0.029)	(0.021)
Inno_Pc_Or_Mk	0.010	−0.106***	0.001
	(0.013)	(0.036)	(0.027)
Inno_Pd_Pc_Or_Mk	0.015*	−0.138***	0.024
	(0.008)	(0.022)	(0.016)
Observations	15,020		
Log-likelihood	−16,811.8		
Wald	2045.6		
P-value	0.00		
McFadden	0.09		
Nagelkerke	0.22		
Akaike	33,918		
Schwarz	35,037		

Table 3 displays the AMEs obtained from the three specifications of the multinomial model of equation (1) in panels A, B, and C, respectively. The dependent variable, $Credit\_Demand\_Mot_i(y)$, is a categorical one that codes the following SME outcomes with respect to bank loans over the previous 6 months: (y_1) applied; (y_2) did not apply because of fear of rejection; (y_3) did not apply because of sufficient internal funds; (y_4) did not apply for other reasons. Applied (y_1) is used as a benchmark.
The AMEs for the firm-level and time and country controls are not reported in panels B and C because they are the same as those displayed in panel A. Standard errors are in parentheses.
Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1.

All in all, except for the few exceptions reported above, it seems that none of the various innovation profiles that SMEs can have are correlated with the perceived risk of being rejected: a suggestion that we will have to verify looking at credit supply in Section 4.2.

Before moving on to that, let us note that panel A of Table 3 shows that it is the availability of internal resources (column 3.b) that, in driving the decision to refrain from requesting credit, matters more for innovative than non-innovative firms More precisely, being a generic innovator reduces by nearly 6% (5.6% with respect to non-innovators) the chance that SMEs refrain from requesting credit because they have internal finance available. In other words, in the case of innovative SMEs, the substitution effect that internally available resources could arguably have on the demand for external credit—a substitution to which the choice of not requesting credit because of internal funds naturally alludes—appears to work to a lower extent. This is an interesting result that confirms and further specifies our previous results about the greater financial needs of innovative SMEs (Table 2). In the same respect, column 3.b of panel B reveals that the choice to not request credit because of available internal resources negatively correlates with (that is, it reduces for) both technological and non-technological innovators but with an interesting specification: consistent with Table 2, the substitution effect entailed by the pecking order theory works more for the latter than for the former as the relative status makes the substitution diminish by 6.2% and 4.7%, respectively.

Looking at panel C, Table 3 reveals that the reduced extent to which internal finance could be thought to substitute external finance is common to nearly all innovation typologies observed. Indeed, the only cases in which being an innovator does not correlate with not resorting to external credit because of internal funds (with respect to non-innovators) are represented by single innovators—with the notable exception of organizational ones—and by SMEs that integrate product innovations with innovations in the most functionally proximate domain (marketing innovation).[22] Once more confirming and specifying the results of Table 2, it is the extent to which firms resort to innovation that might emerge as decisive in increasing their financial needs, to the point of making internal funds insufficient to refrain from requesting external funds. It is a wide rather than restricted innovation involvement that possibly makes SMEs' financial needs increase so much as to render the substitution between internal and external finance "stickier." As a further confirmation of this result, note that the negative AME on the decision to not apply because of available internal funds is among the highest for the threefold innovative profiles and definitively the highest for the full fourfold innovators. With respect to these, the chance that available internal funds could discourage an external credit application reduces by as much as 14 (13.8) percentage points (with respect to non-innovators), confirming the highest financial need we detected for them in Table 2.

In conclusion, let us note that it is only in panel C that reasons other than being discouraged and having internal resources correlate positively with the decision to not request credit and that this occurs for single organizational innovators (*Inno_Or*) and for process and marketing innovators (*Inno_Pr_Mk*) (column 3.c). While further research and more detailed data are required to understand the reasons these two profiles refrain from applying, the interplay between internal and external resources to which the pecking order theory refers is actually the most relevant motivation leading innovative SMEs to apply (or not apply) for external credit.

The fact that innovative SMEs request more credit than non-innovative ones and that they refrain from doing so because of internally available resources is the first result that our model suggests regarding the relationship between innovation and credit demand. A possibly more important result, however, is the specificity of these outcomes, which crucially depend on the kind of innovations that SMEs introduce and/or combine. Indeed, while previous results seem to hold more—if not exclusively—for firms that combine more types of innovation (e.g., three rather than two), various exceptions suggest that the complexity of pursuing specific innovative domains and/or combining certain kinds of them accounts for our results in addition to, and possibly more than, their simple intensity. As we will see, this is a result that our robustness checks seem to confirm and suggests that more attention needs to be paid to the heterogeneous financial needs that SMEs must face to pursue different innovation profiles.

4.2 Credit supply

4.2.1 Heckit model

As for the supply of credit that SMEs eventually receive from banks, its analysis is carried out by estimating equation (2) with a probit model with sample selection *à la* Heckman (*Heckit*), whose first ladder uses equation (1).[23] As previously mentioned, the available data allow us to capture credit supply by looking at the complementary situation of firms facing a financial constraint because they were refused their loan application or refused it themselves as being too costly (*Credit_Constraint*).

22 In spite of the negative sign, the coefficient is also hardly significant for the threefold innovators marked by *Inno_Pd_Pc_Or*.

23 The Wald tests we present at the bottom of Table 4 show that we can reject the null hypothesis of independent equations at the standard significance level. These results clearly justify the Heckman selection approach we have adopted.

Table 4. Being credit-constrained: Heckit model, output equation (lagged regressors, $t-1$), average marginal effects

	(4.a)	(4.b)	(4.c)
Inno	0.015***		
	(0.005)		
Inno_Tech		0.016***	
		(0.005)	
Inno_NTech		0.011**	
		(0.006)	
Inno_Pd			0.005
			(0.007)
Inno_Pc			0.003
			(0.010)
Inno_Or			0.015**
			(0.006)
Inno_Mk			0.014*
			(0.007)
Inno_Pd_Pc			0.012
			(0.007)
Inno_Pd_Or			0.006
			(0.009)
Inno_Pd_Mk			−0.006
			(0.011)
Inno_Pc_Or			0.012
			(0.009)
Inno_Pc_Mk			0.025*
			(0.013)
Inno_Or_Mk			−0.001
			(0.009)
Inno_Pd_Pc_Or			0.006
			(0.009)
Inno_Pd_Pc_Mk			0.012
			(0.009)
Inno_Pd_Or_Mk			0.034***
			(0.009)
Inno_Pc_Or_Mk			0.026***
			(0.010)
Inno_Pd_Pc_Or_Mk			0.032***
			(0.006)
Profit_change	−0.009**	−0.009**	−0.008***
	(0.004)	(0.004)	(0.002)
Leverage_down	0.004	0.004	0.002
	(0.005)	(0.005)	(0.004)
Public_finance	−0.031***	−0.031***	−0.027***
	(0.009)	(0.009)	(0.005)
Single/family_owner	0.005	0.005	0.004
	(0.005)	(0.005)	(0.005)
Age	−0.004	−0.004	−0.003
	(0.004)	(0.004)	(0.003)
Size	−0.009*	−0.009*	−0.007**
	(0.005)	(0.005)	(0.003)
Export	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)
Exper_growth	−0.003	−0.003	−0.003
	(0.003)	(0.003)	(0.002)
Expect_ growth	0.002	0.002	0.001
	(0.003)	(0.003)	(0.002)
Manufacturing_etal	−0.003	−0.003	−0.001
	(0.005)	(0.005)	(0.004)

(continued)

Table 4. (Continued)

	(4.a)	(4.b)	(4.c)
Construction	0.011*	0.012*	0.010**
	(0.006)	(0.006)	(0.005)
Trade	−0.001	−0.001	0.000
	(0.005)	(0.005)	(0.004)
Time effects	Yes	Yes	Yes
Country effects	Yes	Yes	Yes
Observations	12,178	12,178	12,178
Selected	4115	4115	4115
Log-likelihood	−8255.0	−8250.5	−8224.1
Wald test	152.4	152.5	185.4
P-value	0.00	0.00	0.00
Rho	0.71	0.71	0.81
Wald test indep. eqns.	4.25	4.29	10.06
P-value	0.04	0.04	0.00
Akaike	16,646	16,641	16,640
Schwarz	17,150	17,159	17,351

Table 4 reports the AMEs calculated from the three specifications (4.a., 4.b, 4.c) of the output equation of the Heckit model (equation 2), with the dependent dummy variable *Credit_Constraint*$_i$ taking a value of 1 if the firm is financially constrained and 0 otherwise. The exclusion restriction variable, i.e., the independent status of the firm, is omitted. The estimated coefficients for the first stage of the Heckit model are reported in Table A2 in the Appendix. Standard errors are in parentheses.
Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 4 illustrates the AMEs of the expected determinants of this credit constraint by integrating the regressors used in equation (1) with the usual three kinds of innovation profile: generic (column 4.a), technological vs. non-technological (column 4.b), and specific—using the 15 innovative profiles we have identified (column 4.c)—with respect to the benchmark case of fully non-innovative firms. As in the analysis of credit demand, in order to reduce potential endogeneity problems, our focal variables are lagged by one period.[24]

Before moving to the innovation variables, the results regarding the controls deserve some comment. As expected, SMEs that have experienced an increase in profit and thus presumably appear "healthy" to lenders are less likely to (declare to) have been credit-constrained, while their decrease in leverage does not affect this outcome. A positive change in access to public support also correlates negatively with the SMEs' probability of not obtaining external credit, suggesting a possible certification/signaling effect of government subsidies on SME access to bank finance (Li *et al.*, 2019). Consistent with previous studies (Petersen and Rajan, 1994; Berger and Udell, 1995; Mina *et al.*, 2013; Acharya and Xu, 2017; Andrieu *et al.*, 2018), larger SMEs are less likely to be credit-constrained, while their age does not seem to play a role in the same respect. Overall, these results are generally consistent with those of the extant literature. Exceptions could be due to the fact that unlike other studies, our own study focuses only on bank loans rather than on external financing more broadly. For example, across the 11 countries that we consider, the sensitivity of banks to firm age is not significant, whereas the extant literature shows that age is significant in accounting for the decisions of other kinds of external financiers (e.g., venture capitalists or business angels) (Bonini *et al.*, 2019).

Coming to the innovation variables, the first specification (column 4.a) of Table 4 shows that innovative SMEs of any kind are significantly more likely to be credit-constrained than non-innovative ones. When a large set of countries is considered, like that of our sample, the mixed evidence that emerges from comparing the results of previous studies of various individual countries (e.g., Mina *et al.*, 2013; Hain and Christensen, 2020) becomes more clear-cut: having introduced any type of innovation is associated with a higher probability of SMEs being credit-constrained, although of no more than 1.5%. Quite interestingly, the detected constraint

24 Results for the first stage are available in the Appendix (Table A2).

appears to be more strongly correlated with technological (1.6%) than non-technological innovators (1.1%), suggesting that from a supply-side perspective as well, it is the higher risk of successfully introducing new products and processes that makes the difference (column 4.b).

Mimicking what emerged from the credit demand side, the AMEs on credit supply also get larger when the specific innovation profiles of the requesting firms are considered, and once more, the largest AMEs are for the most extensive of these profiles (column 4.c). Differently from credit demand, however, the innovative extent that makes SMEs credit-constrained is greater than that making them more demanding of external credit. While a combination of two (selected) innovation typologies is required to increase the financial needs of SMEs with respect to their non-innovative counterparts (see Table 2), as previously discussed, for them to also be financially constrained the number of innovation typologies required is higher. Indeed, such a case requires the pooling of at least three kinds of innovation typologies to emerge, and these must be of a certain kind, namely those with a non-technological bias (*Inno_Pd_Or_Mk* and *Inno_Pc_Or_Mk*). Furthermore, the highest marginal effect on the occurrence of a credit constraint is exerted by what we call full innovators, combining all of the innovation typologies on our spectrum.[25] For these "super-complex" innovators, the probability of getting constrained in fact increases by 3.2 percentage points with respect to non-innovators.

All in all, it seems that the extent to which SMEs are involved in innovation (typologies) along the innovation profile ladder affects their credit demand more "promptly" than their credit supply. In other words, extending the spectrum of innovation typologies has a more pervasive effect on credit demand than on credit supply, and once more the elements of the spectrum appear to matter, as confirmed by our robustness checks. On the reverse side of the coin, not only is "a little innovation a good thing" in financial terms (see Section 2) but "a single (kind of) innovation" also appears beneficial in order to not be credit-constrained.

4.2.2 Heckman multinomial model

Coming to the extent to which innovative firms can get credit-constrained, Table 5 shows the AMEs of its determinants by estimating equation (2) with a Heckman multinomial probit model in which the benchmark case (credit constraint, y_1) is contrasted with the cases of partial (y_2) or full acceptance of the loan application (y_3), reported in columns 5.a and 5.b, respectively.[26] As in the previous cases, in order to reduce potential endogeneity, all of the relevant explanatory variables are lagged to time $t-1$.[27]

Panel A (Table 5) shows that unlike other SME characteristics that could provide banks with positive signals about their financial reliability and thus account for the larger probability of a full acceptance (with respect to a credit constraint)—such as an increase in profit and in financial support from the public sector—being an innovator has a coefficient with an opposite sign: the chance of getting fully financed reduces by about 6%, confirming that a generic innovation status could be perceived as risky by banks (column 5.b). On the other hand, the same generic status of innovator does not significantly correlate with the chance of being only partially financed (column 5.a), suggesting an important specification of the extent to which innovative SMEs are financially constrained. Our results are consistent with a situation in which banks are more selective in the decision to fulfill the credit requests of innovative firms. However, an innovative status does not appear to reduce (or to increase) the banks' perception that requesting firms are worthy of at least

25 The only exception is represented by the case of single organizational and marketing innovators but with a significance and AME that are both low.

26 AMEs for the benchmark case of being credit-constrained are consistent with those of the Heckit model in Table 4 and are available from the authors upon request. While SAFE would allow us to distinguish a moderate (less than 75% of the request) and an intense (more than 75%) type of partial acceptance, we have opted to collapse the two into a unique category, "partially received," as we do not detect significant differences in the estimated marginal effects between the partially accepted ($\leq$75%) and the mostly accepted (>75% and <100%) categories.

27 We should bear in mind that in the multinomial probit model with sample selection, the marginal effect of a predictor in the observed sample is made up of two components: a direct effect, due to the coefficient in the outcome equation, and an indirect one linked with the selection process. The size of these two effects depends on the particular setting, but the magnitude, sign, and statistical significance of the marginal effect might all be different from those of the estimate coefficient in the outcome equation; this point "appears frequently to be overlooked in empirical studies" (Greene, 2012: 875).

Table 5. Credit received by amount: Heckman multinomial probit model, output equation (lagged regressors, $t-1$), average marginal effects

	(5.a) Partially received (y_2)	(5.b) Fully received (y_3)
Panel A		
Inno	0.026	-0.058^{***}
	(0.027)	(0.015)
Profit_change	−0.020	0.043^{***}
	(0.027)	(0.011)
Leverage_down	−0.021	−0.008
	(0.029)	(0.017)
Public_finance	−0.062	0.141^{***}
	(0.084)	(0.024)
Single/family_owner	0.027	−0.027
	(0.018)	(0.021)
Age	−0.015	0.033^{**}
	(0.032)	(0.013)
Size	0.006	0.041^{***}
	(0.048)	(0.015)
Export	0.008	−0.012
	(0.009)	(0.007)
Exper_growth	−0.001	0.012
	(0.016)	(0.010)
Expect_ growth	−0.001	−0.004
	(0.008)	(0.010)
Manufacturing_etal	0.005	0.013
	(0.022)	(0.018)
Construction	0.009	−0.035
	(0.023)	(0.023)
Trade	0.029^{*}	−0.016
	(0.017)	(0.021)
Time effects	Yes	Yes
Country effects	Yes	Yes
Observations	12,178	
Selected	4115	
Log-likelihood	−9713.6	
Wald test	1246.1	
P-value	0.00	
Akaike	19,631	
Schwarz	20,387	
Panel B		
Inno_Tech	0.035	-0.068^{***}
	(0.036)	(0.023)
Inno_NTech	0.021	-0.055^{***}
	(0.018)	(0.015)
Time effects	Yes	Yes
Country effects	Yes	Yes
Observations	12,178	
Selected	4115	
Log-likelihood	−9708.9	
Wald test	1236.9	
P-value	0.0	
Akaike	19,628	
Schwarz	20,406	
Panel C		
Inno_Pd	0.016	−0.027
	(0.021)	(0.026)
Inno_Pc	−0.039	0.031
	(0.038)	(0.039)

(Continued)

Table 5. (Continued)

Inno_Or	0.036	-0.079^{***}
	(0.031)	(0.026)
Inno_Mk	0.009	−0.041
	(0.028)	(0.032)
Inno_Pd_Pc	0.037	-0.060^{**}
	(0.026)	(0.028)
Inno_Pd_Or	0.050^{*}	−0.048
	(0.028)	(0.035)
Inno_Pd_Mk	0.054	−0.045
	(0.040)	(0.043)
Inno_Pc_Or	0.018	−0.034
	(0.029)	(0.034)
Inno_Pc_Mk	0.053	-0.113^{*}
	(0.061)	(0.059)
Inno_Or_Mk	0.059	−0.060
	(0.037)	(0.037)
Inno_Pd_Pc_Or	0.038	−0.053
	(0.029)	(0.032)
Inno_Pd_Pc_Mk	−0.010	−0.012
	(0.032)	(0.037)
Inno_Pd_Or_Mk	0.020	-0.102^{***}
	(0.037)	(0.037)
Inno_Pc_Or_Mk	0.020	-0.077^{*}
	(0.035)	(0.041)
Inno_Pd_Pc_Or_Mk	0.033	-0.106^{***}
	(0.028)	(0.027)
Time effects	Yes	Yes
Country effects	Yes	Yes
Observations	12,178	
Selected	4115	
Log-likelihood	−9678.8	
Wald test	1382.6	
P-value	0.0	
Akaike	19,646	
Schwarz	20,713	

Table 5 reports the AMEs obtained from the three specifications of the output equation of the Heckit model (equation 2), in panels A, B, and C, respectively. The dependent variable, $Credit\_Received\_Amnt_i\,(y)$, is a categorical one that codes the following cases: (1) did not receive the requested financing, either because the loans were rejected or refused (y_1); (2) received the requested financing only partially (y_2); (3) received the requested financing completely (y_3). (1) is used as the benchmark case. The AMEs for the controls are not reported in panels B and C because they are the same as those displayed in panel A.
The estimated coefficients for the first stage of the Heckman multinomial probit model are reported in Table A2 in the Appendix. Standard errors are in parentheses.
Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

partial credit. In short, the same status apparently reduces but does not cancel out the chance that requesting firms could be deemed worthy of credit by banks.

When we move to the results regarding technological and non-technological innovation profiles, panel B (Table 5) shows that none of them significantly affect the probability of being partially financed with respect to the benchmark case of being constrained (column 5.a), confirming the results obtained looking at generic innovators. The significantly negative coefficients that *Inno_Tech* and *Inno_NTech* reveal with respect to the outcome of full acceptance of the credit requested is also consistent (column 5.b). Not surprisingly, however, it is technological innovators that have a larger negative effect on the same outcome (6.8% vs. 5.5% in absolute values), possibly because the “hard” kinds of innovations like product and process innovations could be perceived as more risky by banks.

The previous picture is basically confirmed when we disentangle the 15 kinds of innovation profile we have identified. Panel C of Table 5 shows that for all of these innovation profiles, the probability of getting partially financed does not decrease with respect to the benchmark and does not significantly increase either (column 5.b). An interesting specification emerges when we look at the probability of SMEs being fully financed, however. Consistent with the main argument of this paper, it is the specific kind of introduced innovation that makes firm innovativeness correlate with the outcome of full credit supply. At first sight, and consistent with what we found in terms of credit demand and supply above, it is the intensity of this innovativeness that seems to matter: super-complex innovators (*Inno_Pd_Pc_Or_Mk*) show the highest marginal reduction of full acceptance (−10%) and higher is also the reduction of complex non-technological innovators that integrate product innovations (*Inno_Pd_Or_Mk*). However, intensity is apparently not the only relevant issue, as a significantly negative correlation with the outcome at stake emerges also with respect to fully technological innovators (*Inno_Pd_Pc*) and single organizational ones (*Inno_Or*).

In conclusion—and corroborating the results we obtained for the credit demand side—it is both the extent to which SMEs are involved in innovation and the specific spheres in which they do so that matter the most to account for the extent to which their credit demand is accepted. This is an additional novel result of this paper and suggests a new light under which the financial constraints of innovative SMEs should be considered in future analyses and policy actions.

4.3 Robustness checks and additional results

As we noted in illustrating the outcomes of our previous analysis, the correlation between the propensity of innovative SMEs to request more credit and to get more financially constrained than non-innovators seems to increase with the simple number of innovation typologies they combine. This suggests that such a "typological" innovation intensity could be the key variable, rather than the "complexity" coming from the combination of specific typologies.

The results of the estimates that we have run by replacing our 15 innovation typologies with the four dummies of innovation counts, that is, *Inno1, Inno2, Inno3*, and *Inno4*, seemingly confirm this suggestion for both the demand side and the supply side (see Tables 6 and 7). However, by comparing the two sets of results for each of the two domains, we can appreciate that intensity is only a part of the story and that its exclusive consideration could be misleading.

Starting with credit demand, panel A of Table 6 shows that AMEs are increasingly higher for innovators with progressively more innovation types, from 2.7% for single innovators (*Inno1*) up to 9.0% for super-complex innovators (column 6.A.i), *Inno4*, which is consistent with what we found for *Inno_Pd_Pc_Or_Mk* in Table 2. Going back to Table 2, however, we notice that the only single innovators that actually show a higher propensity to request credit are marketing innovators (*Inno_Mk*) and that the relative AMEs increase only with respect to fully technological "bi-innovators" (*Inno_Pd_Pc*) and organizational innovators that combine product and process innovations (*Inno_Pd_Or* and *Inno_Pc_Or*). Finally, the increase in AMEs for triple innovators is substantial mainly for fully technological innovators that integrate process innovations (*Inno_Pc_Or_Mk*). All in all, this parallel suggests that in understanding the possible impact of innovation on credit demand, the specific nature of the innovation typologies that are combined should be considered along with their number, as we have argued. Still in terms of credit demand, in the same panel, column (6.A.ii) confirms that the count of innovation typologies (*Inno_count*) is significantly positive and that, as suggested by the results of column (6.A.i), the propensity to demand credit grows with the innovation intensity of SMEs in a linear way (the square of *Inno_Count* is not significant).

Intensity in terms of the number of introduced innovation types also emerges as relevant for the unique motivation that we found to justify the SMEs' decision to not seek bank credit, that is, the availability of internal resources (Table 6, panel B). *Inno_Count* negatively correlates with this last decision (column 6.B.v), suggesting that the substitution of internal with external financial resources works progressively less well for more innovation-intensive firms, once more in a linear manner (the square of *Inno_Count* is still not significant). Column (6.B.ii) consistently shows that the absolute value of the AMEs revealed by *Inno1, Inno2, Inno3*, and *Inno4* with respect to the focal motivation increases progressively. However, Table 3 once more reveals that it is neither the number nor the increase in any kind of innovation typology that renders SMEs'

Table 6. Credit demand and intensity of innovation, average marginal effects

	Panel A		Panel B					
	Logit models		Multilogit models					
	Seeking bank credit		Not seeking bank credit by motivation					
			Fear of rejection	Available internal funds	Other reasons	Fear of rejection	Available internal funds	Other reasons
	(6.A.i)	(6.A.ii)	(6.B.i)	(6.B.ii)	(6.B.iii)	(6.B.iv)	(6.B.v)	(6.B.vi)
			(y_2)	(y_3)	(y_4)	(y_2)	(y_3)	(y_4)
Inno1	0.027**		0.000	−0.035***	0.007			
	(0.012)		(0.005)	(0.013)	(0.010)			
Inno2	0.046***		0.007	−0.059***	−0.001			
	(0.012)		(0.005)	(0.014)	(0.010)			
Inno3	0.067***		0.007	−0.073***	−0.004			
	(0.016)		(0.006)	(0.016)	(0.012)			
Inno4	0.090***		0.015*	−0.135***	0.021			
	(0.021)		(0.009)	(0.021)	(0.017)			
InnoCount		0.026**				0.001	−0.025**	−0.005
		(0.011)				(0.005)	(0.012)	(0.009)
InnoCount^2		−0.001				0.001	−0.001	0.002
		(0.003)				(0.001)	(0.003)	(0.002)
Observations	15,020	15,020	15,020			15,020		
Log-likelihood	−8744	−8744	−16,834			−16,836		
Wald test	686.0	685.6	1978.4			2012.7		
P-value	0.00	0.00	0.00			0.00		
McFadden	0.05	0.05	0.09			0.09		
Nagelkerke	0.08	0.08	0.22			0.22		
Akaike	17,564	17,560	33,896			33,887		
Schwarz	17,854	17,835	34,764			34,710		

Table 6 reports the AMEs obtained from the different specifications of equation 1, using the *Inno_count* variable, the innovation intensity, and its squared term.
In the estimates in panel B, *Applied for bank loans* (y_1) is used as the benchmark case.
The AMEs for the controls are not reported for the sake of brevity but are available upon request. Standard errors are in parentheses.
Significance levels: ***$p<0.01$, **$p<0.05$, *$p<0.1$.

innovativeness progressively more correlated (in absolute value) with refraining from requesting credit because of internal resources. The only single innovators for which the correlation is significant are organizational ones (*Inno_Or*); among the bi-innovators, marketing innovators that also implement a product or an organizational innovation (*Inno_Pd_Mk* and *Inno_Or_Mk*) do not show a (fully) significant correlation; the same holds true for triple technological innovators that integrate an organizational innovation in their innovation profile (*Inno_Pd_Pc-Or*), while super-complex innovators (*Inno_Pd_Pc_Or_Mk*) once more exhibit the highest AME, consistent with that revealed by *Inno4*.

Coming to credit supply (Table 7), our main argument about the importance of looking at the complexity of innovation typologies by integrating the analysis of their number with that of their specific nature is also confirmed but with some important nuances (Table 7, panels A and B). Looking at the probability of being credit-constrained, this does not appear to be systematically more correlated with innovation profiles containing progressively more innovation typologies. In column (7.A.i), *Inno2* is not significant, and once more the detected correlation between credit rationing and the number of innovation types maps only partially onto the corresponding profiles of Table 3.[28] This suggests a possible non-linearity in the AME of *InnoCount*, which is confirmed

28 For example, organizational innovators (*Inno_Or*) are still the only single innovators that are apparently more constrained.

Table 7. Credit supply and intensity of innovation, average marginal effects

	Panel A		Panel B			
	Heckit model		Multilogit models			
	Being credit-constrained		Credit received by amount			
			Partially received	Fully received	Partially received	Fully received
	(7.A.i)	(7.A.ii)	(7.B.i)	(7.B.ii)	(7.A.iii)	(7.B.iv)
			(y_2)	(y_3)	(y_2)	(y_3)
Inno1	0.010**		0.014	−0.040**		
	(0.004)		(0.022)	(0.017)		
Inno2	0.006		0.046	−0.056**		
	(0.004)		(0.031)	(0.024)		
Inno3	0.021***		0.019	−0.066***		
	(0.007)		(0.030)	(0.024)		
Inno4	0.041***		0.029	−0.114***		
	(0.010)		(0.045)	(0.034)		
InnoCount		0.003***			0.011	−0.015***
		(0.000)			(0.009)	(0.005)
InnoCount2		0.001***			−0.002	0.001
		(0.000)			(0.002)	(0.000)
Observations	12,178	12,178	12,178		12,178	
Selected	4115	4115	4115		4115	
Log-likelihood	−8243.4	−8206.8	−9700.5		−9700.2	
Wald test	169.5	168.2	1187.5		38.2	
P-value	0.00	0.00	0.00		0.00	
Rho	0.77	0.80				
Wald test of ind. eqns.	6.85	7.18				
P-value	0.01	0.01				
Akaike	16,634.8	16,421.5	19,623.1		19,406.4	
Schwarz	17,183.0	16,451.1	20,445.3		19,428.7	

Table 7 reports the AMEs obtained from the different specifications of equation 2 using the *Inno_count* variable, the innovation intensity, and its squared term.
In the estimates in panel B, *Did not receive the requested financing*, either because the loans were rejected or refused (y_1), is used as the benchmark case.
The AMEs for the controls are not reported for the sake of brevity but are available upon request.
The estimated coefficients for the first stage of the Heckit and Heckman multinomial probit models are reported in Table A3 in the Appendix. Standard errors are in parentheses.
Significance levels: ***$p < 0.01$, **$p < 0.05$.

in column (7.A.ii). The positive sign of $InnoCount^2$ reveals that increasing the number of innovation typologies could actually decrease the risk of SMEs being credit-constrained up to a certain threshold, after which such a risk would actually increase: quite interestingly, up to a certain point being a multi-innovator would seem to provide banks with positive reliability signals but after this point the creditworthiness of innovative SMEs might appear to diminish, as shown in Table 4.

The pattern again becomes linear when we look at the relationship between innovation intensity and the extent to which SMEs are fully financed (panel B of Table 7). Innovation profiles with progressively more types of innovation correlate significantly and negatively with the chance of getting the requested credit fully accepted (column 7.B.ii), to an increasing extent (in absolute values of AMEs) from *Inno1* to *Inno4* (which is still consistent with what we found for super-complex innovators in Table 5) and still with an imperfect mapping in the actual profiles we investigate in Table 5.[29] In column (7.B.iv), $InnoCount^2$ is non-significant and confirms that the relationship is actually linear.

29 For example, as we saw in Table 4 the only bi-innovators for which the probability at stake reduces to an appreciably significant extent with respect to non-innovators is represented by fully technological innovators (*Inno_Pd_Pc*).

5. Conclusions

This paper provides new arguments and evidence regarding the link between innovation and external financing with respect to SMEs. As a first value added to the extant literature on the topic, we extend the standard distinction between innovative and non-innovative SMEs to the consideration of the profiles the latter reveal in terms of the typologies of innovation they introduce and eventually combine: technological vs. non-technological and different kinds of each of these two macro-typologies. Drawing on innovation studies, we argue and expect that SME innovation profiles could have a differential impact on the credit SMEs request and obtain from banks, respectively. As a second value added, we investigate whether innovative SMEs with different profiles behave differently from their non-innovative peers, not only in the extent to which they seek and obtain external finance but also in the motivations and amounts of these respective decisions. Last but not least, extending previous studies mainly carried out with respect to specific country datasets, we address our research questions with respect to a large sample of SMEs in 11 countries in the EU15, observed over the 2014–2019 period.

The results that we have obtained are only partially supportive of existing knowledge about the relationship between finance and innovation and add to it a set of interesting specifications. In contrast to previous country-specific studies (e.g., Mina *et al.*, 2013; Hain and Christensen, 2020), we do find confirmation of the theoretical tenet according to which innovation exacerbates the search for credit by SMEs (Hall and Lerner, 2010). Furthermore, we qualify this tenet in at least two respects. Firstly, with respect to non-innovative ones, innovative SMEs increase their credit demand also and above all with the extent of their involvement in different innovation typologies, with credit demand being larger for complex innovators that combine more and selected types of technological and non-technological innovations. Secondly, increasing SME involvement in different innovation typologies also decreases the extent to which their internal funds are sufficient to make them refrain from requesting external credit. Their innovation profiles instead do not affect the emergence of a discouraged borrower effect in credit demand. Both of these specifications suggest that an important dimension that makes SMEs more credit-seeking and that could thus make their internal financing insufficient is their innovation involvement at the "extensive margin," as this could be captured by different kinds of innovation that SMEs introduce and possibly combine. This dimension has been relatively neglected in previous studies and should be carefully considered to refine our knowledge about how firm innovation affects their finance and about how the latter could turn into a barrier. In this last respect, the same dimension is important for policymakers too, and they should insert it into the information set used to map the aspects of firms' innovative activities that are more likely to generate financial needs they could help fulfill.

As far as the supply side of credit is concerned, consistent with literature predictions (Kerr and Nanda, 2015; Lee *et al.*, 2015) but once more different from some previous country-specific studies, our results show that getting involved in innovative activities boosts the probability that SMEs end up financially constrained as they do not obtain the credit requested. On the other hand, for the sake of getting financed, not only is "a little innovation good," but "a simple" innovation is also good. Indeed, the chance of becoming financially constrained is highest for complex innovators engaging in risky combinations of technological and non-technological changes. While providing firms with an extremely important strategic recommendation to address a potential trade-off between innovation complexity and financeability, policymakers are asked to help innovative SMEs in attenuating the same trade-off. In particular, SMEs that engage in innovation to a greater extent should be on the radar of policymakers in their actions to mitigate financial barriers to innovation. The same kind of strategic and policy implications are implied by our results regarding the extent to which SMEs get financially constrained. Results on the amount of SME credit demand that is financed seem to suggest that a generic innovative status makes banks more selective in their decision to completely fulfill a credit request, but the probability of this decision by banks decreases only with respect to a few, mainly multi-innovation profiles.

In conclusion, we acknowledge some limitations of our study, which the availability of further data could possibly help us address. First of all, our understanding of the relationship between innovation status and external finance for SMEs would benefit from the introduction of additional variables—in particular, of a quantitative and continuous nature with respect to the innovation outcomes, skills, and competencies of the focal firms. Secondly, the analysis could be also enriched by considering data on R&D, patents, and other intangible investments, the lack of data on which we have tried to remedy by employing a broad set of controlling covariates aimed at capturing firm heterogeneity. Thirdly, results could be made more accurate by overcoming the absence of firm identifiers in SAFE, which would then allow it to be linked to other datasets such as balance-sheet data, where detailed information about firm financing are available. Addressing these limitations goes beyond the scope of our study and can provide input for further research.

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Appendix

Table A1. Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	applied_loan															
2	rej_loan															
3	inno	0.05***	0.03**	1												
4	Tech	0.05***	0.03*	0.69***	1											
5	NTech	−0.01	0.01	0.36***	−0.42***	1										
6	Inc	0.06***	0.08***	0.78***	0.75***	0.01	1									
7	Pd	0.01	−0.00	0.22***	0.31***	−0.13***	−0.05***	1								
8	Pc	−0.01	−0.03**	0.17***	0.24***	−0.10***	−0.04***	−0.06***	1							
9	Or	0.01	−0.02	0.25***	−0.29***	0.68***	−0.06***	−0.09***	−0.07***	1						
10	Mk	−0.02**	0.00	0.16***	−0.18***	0.44***	−0.04***	−0.06***	−0.04***	−0.07***	1					
11	Pd_Pc	0.03***	0.01	0.19***	0.27***	−0.11***	0.15***	−0.07***	−0.05***	−0.08***	−0.05***	1				
12	Pd_Or	0.01	0.00	0.14***	0.20***	−0.08***	0.11***	−0.05***	−0.04***	−0.06***	−0.04***	−0.04***	1			
13	Pd_Mk	−0.01	−0.04**	0.14***	0.21***	−0.09***	0.12***	−0.05***	−0.04***	−0.06***	−0.04***	−0.04***	−0.03***	1		
14	Pc_Or	0.04***	−0.02	0.14***	0.20***	−0.08***	0.11***	−0.05***	−0.04***	−0.06***	−0.04***	−0.04***	−0.03***	−0.03***	1	
15	Pc_Mk	−0.01	0.01	0.07***	0.10***	−0.04***	0.06***	−0.03***	−0.02**	−0.03***	−0.02**	−0.02**	−0.02*	−0.02*	−0.02*	1
16	Or_Mk	−0.00	0.03*	0.17***	−0.20***	0.47***	0.14***	−0.06***	−0.05***	−0.07***	−0.05***	−0.05***	−0.04***	−0.04***	−0.04***	−0.02**
17	Pd_Pc_Or	0.03***	0.02	0.16***	0.23***	−0.10***	0.30***	−0.06***	−0.04***	−0.07***	−0.04***	−0.05***	−0.04***	−0.04***	−0.04***	−0.02**
18	Pd_Pc_Mk	−0.01	−0.02	0.13***	0.19***	−0.08***	0.25***	−0.05***	−0.04***	−0.05***	−0.04***	−0.04***	−0.03***	−0.03***	−0.03***	−0.02*
19	Pd_Or_Mk	0.00	0.05***	0.13***	0.19***	−0.08***	0.25***	−0.05***	−0.04***	−0.05***	−0.03***	−0.04***	−0.03***	−0.03***	−0.03***	−0.02*
20	Pc_Or_Mk	0.01	0.02	0.11***	0.16***	−0.07***	0.21***	−0.04***	−0.03***	−0.05***	−0.03***	−0.03***	−0.03***	−0.03***	−0.02***	−0.01
21	Pd_Pc_Or_Mk	0.03***	0.08***	0.19***	0.27***	−0.11***	0.55***	−0.07***	−0.05***	−0.08***	−0.05***	−0.06***	−0.04***	−0.04***	−0.04***	−0.02**
22	Profit_change	−0.01	−0.12***	0.04***	0.05***	−0.02**	0.04***	0.01	0.02**	−0.00	−0.01	0.03***	0.02**	−0.00	−0.00	−0.00
23	Leverage_down	−0.07***	0.04***	0.04***	0.03***	0.01	0.03***	0.02**	0.02*	0.01	−0.01	0.00	0.03***	−0.00	−0.01	0.02**
24	Public_finance	−0.01	−0.21***	−0.01	−0.00	−0.01	−0.02*	0.00	0.02**	0.01	−0.01	0.02**	−0.01	−0.01	−0.01	−0.01
25	Single/Family	−0.01	0.05***	−0.02**	−0.02**	−0.00	0.00	−0.02**	−0.02***	−0.04***	0.03***	−0.03***	−0.02**	0.01	−0.00	0.01

(continued)

Table A1. (Continued)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
26	Independent	0.02**	0.03**	−0.03***	−0.03***	−0.00	0.01	−0.03***	−0.02**	−0.04***	0.04***	−0.04***	−0.04***	0.02**	−0.03***	−0.01	
27	Age	0.05***	−0.04**	−0.05***	−0.04***	−0.00	−0.06***	−0.00	0.00	−0.00	0.00	0.01	−0.01	−0.02*	0.00	−0.02*	
28	Size	0.14***	−0.16***	0.07***	0.05***	0.02**	0.01	0.03***	0.07***	0.08***	−0.05***	0.05***	0.01	−0.05***	0.04***	−0.01	
29	Export	0.08***	−0.04**	0.14***	0.18***	−0.06***	0.12***	0.10***	0.03***	−0.02**	−0.05***	0.10***	0.04***	0.01	0.01	−0.02*	
30	Exper_growth	0.03***	−0.11***	0.10***	0.11***	−0.02**	0.11***	0.01	0.03***	−0.00	−0.01	0.04***	0.01	0.01	0.01	−0.00	
31	Exp_ growth	0.03***	−0.07***	0.16***	0.17***	−0.02**	0.19***	0.02**	−0.00	−0.03***	−0.01	0.05***	0.03***	0.04***	−0.00	0.01	
		16	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**
16	Or_Mk	1															
17	Pd_Pc_Or	−0.05***	1														
18	Pd_Pc_Mk	−0.04***	−0.04***	1													
19	Pd_Or_Mk	−0.04***	−0.03***	−0.03***	1												
20	Pc_Or_Mk	−0.03***	−0.03***	−0.02***	−0.02***	1											
21	Pd_Pc_Or_Mk	−0.05***	−0.05***	−0.04***	−0.04***	−0.03***	1										
22	Profit_change	−0.02**	0.02***	0.02***	−0.01	−0.01	0.01	1									
23	Leverage_down	0.01	0.00	−0.00	0.00	0.00	0.01	0.18***	1								
24	Public_finance	−0.02**	0.01	0.01	−0.03***	0.01	−0.01	0.20***	0.06***	1							
25	Single/Family	0.02**	0.00	0.01	−0.00	0.01	0.02**	−0.03***	−0.00	−0.02***	1						
26	Independent	0.02**	0.00	0.02**	0.01	0.01	0.04***	−0.03***	−0.02***	−0.04***	0.38***	1					
27	Age	−0.01	−0.03***	−0.01	−0.02*	−0.02*	−0.02**	−0.02***	0.01	0.01	−0.01	0.01	1				
28	Size	−0.03***	0.03***	−0.02*	−0.02**	−0.01	−0.04***	0.14***	0.05***	0.09***	−0.23***	−0.23***	−0.13***	1			
29	Export	−0.04***	0.09***	0.02*	0.01	0.02*	0.01	0.05***	0.02***	0.04***	−0.09***	−0.13***	0.04***	0.29***	1		
30	Exper_growth	−0.03***	0.05***	0.06***	0.02***	0.01	0.04***	0.46***	0.12***	0.29***	−0.02	−0.02	−0.03	0.09***	0.08***	1	
31	Exp_ growth	0.00	0.08***	0.06***	0.05***	0.01	0.09***	0.26***	0.05***	0.12***	0.03	0.03*	0.08***	0.07***	0.09***	0.36***	1

Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
For the sake of readability, the prefix *inno* has been omitted in all cases except the generic innovator variable.

Table A2. Coefficients for the first stage of the Heckit and Heckman multinomial probit models

	(1)	(2)	(1)	(2)	(1)	(2)
Inno	0.236***	0.096***				
Inno_Tech			0.256***	0.127***		
Inno_NTech			0.188**	0.025		
Inno_Pd					0.087	0.103**
Inno_Pc					0.044	0.021
Inno_Or					0.245**	0.003
Inno_Mk					0.224*	0.138**
Inno_Pd_Pc					0.196	0.150***
Inno_Pd_Or					0.098	0.230***
Inno_Pd_Mk					−0.097	−0.031
Inno_Pc_Or					0.185	0.200***
Inno_Pc_Mk					0.403*	0.028
Inno_Or_Mk					−0.021	−0.031
Inno_Pd_Pc_Or					0.093	0.118*
Inno_Pd_Pc_Mk					0.187	0.129*
Inno_Pd_Or_Mk					0.544***	0.133*
Inno_Pc_Or_Mk					0.433***	0.210**
Inno_Pd_Pc_Or_Mk					0.523***	0.208***
Profit_change	−0.136***	−0.008	−0.136***	−0.008	−0.126***	−0.008
Leverage_down	0.059	−0.262***	0.056	−0.264***	0.037	−0.264***
Public_finance	−0.478***	−0.018	−0.478***	−0.018	−0.445***	−0.017
Single/Family_owner	0.075	0.109***	0.076	0.109***	0.065	0.106***
Age	−0.058	0.083***	−0.057	0.084***	−0.045	0.083***
Size	−0.143***	0.276***	−0.141**	0.278***	−0.110**	0.281***
Export	0.026	0.020	0.024	0.017	0.027	0.017
Exper_growth	−0.046	0.068***	−0.047	0.066***	−0.044	0.066***
Exp_growth	0.30	0.024	0.028	0.021	0.015	0.019
Manufacturing_etal	−0.049	0.110***	−0.053	0.103***	−0.024	0.106***
Construction	0.176**	0.063	0.180**	0.068	0.173**	0.067
Trade	−0.013	0.093***	−0.011	0.095***	0.008	0.098***
Independent		0.160***		0.159***		0.157***
Constant	−0.698	−2.000***	−0.694	−1.993***	−0.882**	−1.977***
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,178		12,178		12,178	
Log-likelihood	−8255		−8250		−8224	
Chi-squared	152.4		152.5		185.3	
Prob	0.00		0.00		0.00	

Table A2 reports the estimated coefficients for the first stage of the Heckit and Heckman multinomial probit models. The AMEs for the output equations are displayed in Tables 4 and 5, respectively. Standard errors are in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05.$, $^{*}p < 0.1$.

Table A3. Robustness check: coefficients for the first stage of the Heckit and Heckman multinomial probit models

	(1)	(2)	(1)	(2)
Inno1	0.173**	0.059*		
Inno2	0.118	0.093***		
Inno3	0.333***	0.134***		
Inno4	0.538***	0.200***		
InnoCount			0.044***	0.048**
InnoCount^2			0.020***	−0.001
Profit_change	−0.130***	−0.007	−0.128***	−0.007
Leverage_down	0.045	−0.262***	0.041	−0.260***
Public_finance	−0.452***	−0.017	−0.445***	−0.016
Single/Family_owner	0.079	0.108***	0.073	0.109***
Age	−0.055	0.084***	−0.047	0.082***
Size	−0.117**	0.279***	−0.111*	0.280***
Export	0.025	0.019	0.022**	0.017
Exper_growth	−0.046	0.067***	−0.047	0.067***
Exp_growth	0.012	0.019	0.008	0.020
Manufacturing_etal	−0.034	0.112***	−0.021	0.113***
Construction	0.187**	0.067	0.182***	0.062
Trade	0.001	0.094***	0.010	0.094***
Independent		0.156***		0.153***
Constant	−0.787*	−1.985***	−0.814	−1.971***
Country Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	12,178		12,178	
Log-likelihood	−8243		−8207	
Chi-squared	169.5		168.2	
Prob	0.00		0.00	

Table A3 reports the estimated coefficients for the first stage of the Heckit and Heckman multinomial probit models. The AMEs for the output equations are displayed in Table 7. Standard errors are in parentheses.
Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.