Financial support to innovation: the role of European development financial institutions

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Abstract

This paper explores the role of Development Financial Institutions (DFIs) in supporting innovation by facilitating the access to finance for start-ups and high-growth small and medium enterprises. After having mapped the population of DFIs in Europe, we benchmark their portfolio of equity deals to those of other European financial institutions (venture capital and private equity). We build a unique sample of European 12,437 M&As within the 2008–2017 period and for each target company we match the related patenting and economic data. We obtain a dataset of 80,713 yearly observations which allows us to empirically analyse the pre and post-deal patenting activity of companies targeted by both DFIs and other financial institutions. Our findings show that the target company patenting performance improves after receiving the support of financial institutions, and this effect is on average higher when DFIs participate to the equity deal. We also find that partnerships among DFIs and other financial institutions are associated with the best patenting performance of the target companies. These results are confirmed when a propensity score matching technique is adopted to address biases associated to the potential endogenous selection of the target company.

Keywords: Development banking; Development Financial Institutions; public-private partnership; equity deals; patenting activity; financial support to innovation

1. Introduction

The decade since the onset of the global financial crisis has increased interest in development banking to promote growth, boost investment and support structural changes in the economies. Specifically, with public finances often being stretched, and the banking sector undergoing re-assessing, restructuring and adjusting of business strategies and models, development financial institutions have been seen as a way to improve access to finance, particularly for start-ups and high-growth small and medium-sized enterprises (SMEs; European Parliament 2016, Wruuck 2015). These enterprises, which need capital to invest in research and innovation to develop new products and services and to facilitate internationalization, typically find it difficult to access finance, due to a lack of guarantees, collaterals and track records of profitable investments, or because they are operating in high-risk and innovative sectors (OECD 2015). Difficulties in accessing finance are also due to a general deleveraging process in the commercial banking sector after the 2008 crisis, resulting from a legacy of problematic bank assets, as well as strengthening of new European Union (EU) regulations concerning capital adequacy (BIS 2018).

Although development financial institutions have traditionally been part of the economic policy toolkit and the financial market landscape (Diamond 1957; de Aghion 1999), after the 2008 crisis, their role in mitigating market failures and ensuring the functioning of the market has strengthened, and development financial institutions have become more active in funding high-risk projects, stimulating innovation and supporting a response to new global challenges. Several member states of the EU have reorganized their existing development financial institutions or set up new institutions with the aim of leveraging their potential by attracting additional private investments, strengthening the longer-term availability of finance for SMEs and start-ups and boosting growth (European Commission 2014; OECD 2017, 2018a, 2018b).

To the best of our knowledge, in spite of their increasing activity and role, to date, there is no empirical evidence on the role of development banks in supporting innovation. More generally, studies on development banks are scant, and apart from theoretical contributions discussing their existence (Musacchio et al. 2017; Mazzuccato and Penna 2016; Bleda and Del Rio 2013), they are mainly focused on the lending activity of single institutions (Robinson 2009; Clifton, Diaz-Fuentes, & Revuelta 2014; Clifton, Diaz-Fuentes, & Gomez 2018; Tuijnman 2009), or their political connections (Frigerio and Vandone 2020; Lazzarini et al. 2015).

We wish to fill this gap with a detailed analysis on the recourse of development financial institutions to equity deals as a mechanism for financing innovation. The rationale behind the specific focus on equity deals is that while financial instruments and services used to support capital expenditure and working capital typically vary from loans to guarantees and advisory services, early-stage innovation financing mainly consists of equity investment and co-investments in the form of development capital and corporate venturing. Specifically, the aim of our paper is to analyse the portfolio of investments made by development banks in support of this type of operation and to investigate how the participation of development banks as investors in equity deals affects the patenting activity of the target companies.

We measure innovation using firms' patent activity, that is, the total number of patent applications filed every year by each target enterprise company composing our sample. Several empirical papers have previously investigated the role of financial institutions in supporting innovation using patents applications as a good proxy for inventions and innovative ideas (Mann and Stager 2007; Bertoni et al. 2010; Hall and Lerner 2010; Hirukawa and Ueda 2011; Arqué-Castells 2012; Geronikolaou and Papachristou 2012; Acharya et al. 2014; Faria and Barbosa 2014; Bertoni and Tykvová 2015).

The main reason why a vast body of empirical literature uses patents to measure firms' innovative activity is the recognition that in spite of being an imperfect proxy of innovation,[1] patents have several

[1] The shortcomings of this proxy have been discussed in previous literature. In particular: (i) many patents are not always translated into innovative products which are successfully introduced to the marketplace; (ii) patent measures can be biased in the case that firms strategically decide not to patent their innovations; (iii) patents can be filed for strategic

strengths. First, patent counts are a measurable direct outcome of the firm's research and development (R&D) process, which highly correlate with other potential measures of innovative activity, such as R&D spending or the announcement of new products (Hagedoorn and Cloodt 2003). They are publicly available documents, which are collected on a regular basis and present very long historical time series, thus allowing for international comparison (Griliches 1990). They can be considered a reliable proxy of innovation activity especially in manufacturing industries (Kleinknecht et al. 2002; Hipp and Grupp 2005). Furthermore, in the cases we are considering of infant companies requiring the financial support of development financial institutions to develop their products and businesses, it is likely that the patenting activity is motivated by the genuine intent to legally protect the value of their R&D efforts.

Data on equity deals are collected from the Zephyr database, produced by Bureau van Dijk (BvD), while data on patent activity and other characteristics of the target companies are obtained from the ORBIS database (BvD). The dataset refers to equity deals within the 2008–2017 period with at least one acquirer headquartered in Europe. Two main types of equity deals are considered – venture capital and private equity – and deals performed by development financial institutions are benchmarked to deals performed by other financial institutions. The final sample refers to 12,437 equity deals, about ten percent of which count at least one development financial institution among the acquirers.

Results from our analysis show that patent activity is on average higher when development financial institutions are among the investors providing financial support to the target companies of equity deals. Moreover, the best performances in terms of patent activity are associated with partnerships among development financial institutions and other (non-development) financial institutions. A battery of robustness tests confirms our results. In particular, the adoption of alternative

reasons to increase economic barriers against market competitors; and (iv) a race to the patent behavior may be adopted in order to increase the costs of the competitors activity or to prevent a competitor to use the technology (Archibugi and Pianta 1996; Griliches 1990; Langinier 2004; Kleinknecht et al. 2002).

measures for the main variables of our interest and the recourse to alternative econometric approaches produce very consistent findings.

The remainder of the paper is organized as follows. Section 2 illustrates the specificities of development banks and their role in financing innovation. Section 3 describes the dataset and the main characteristics of our sample. Section 4 presents the estimation strategy and results. Section 5 presents a battery of robustness checks, and Section 6 concludes.

2. The role of development banks in financing innovation

Development banks play a relevant role in the economy, since they provide financial services to strategic sectors, sustain growth during periods of recession and invest in physical and technological infrastructures. More recently, they have been increasingly addressing their activity to yield social payoffs and positive externalities for society as a whole, such as stimulating technological innovation and channelling funds to long-term global societal challenges, such as climate change, renewable and environmental-friendly energy and food security (World Bank 2018).

Indeed, development banks typically fund high risk projects that private banks may not finance if there are difficulties in evaluating the business, the innovation process and therefore the expected returns and their distribution over time. Alternatively, private banks may not finance such projects if there is a lack of guarantees and collaterals, or a lack of a track-record of profitable investments, which is typically the case of high-tech or new industries, start-ups, young entrepreneurial activities and R&D investments. In order to enable firms to access the capital necessary for growth, development banks may step in using a range of instruments: direct or indirect loans, syndicated loans, credit guarantees and equity tools such as venture capital, private equity, seed capital financing and mezzanine financing (Bottazzi et al. 2004; Broccolini et al. 2020; Tykvová 2006; Musacchio et al. 2017; Mazzuccato and Penna 2016; Bleda and Del Rio 2013).

Development financial institutions intervene in the financing of start-ups and SMEs at several levels and with several instruments. Indeed, the 2014 Investment Plan for Europe, aimed at facilitating access to finance for start-ups and SMEs, is managed and implemented by the European Investment Bank (EIB), on behalf of and in partnership with the European Commission, and then realized at national level with the help of national promotional banks, such as the Kreditanstalt fuer Wiederaufbau (KfW), Caisse des Dépôts et Consignations (CDC) and the Cassa Depositi e Prestiti (CDP), given their particular expertise and their knowledge of the local context as well as national policies and strategies. Moreover, in 2014, together with the European Commission, the EIB launched the InnovFin – EU Finance for Innovators, aimed at financing research and innovation by companies, small to large, young to well-established and financing the promoters of research. The programme also includes thematic products addressing the specific financing needs of certain innovative sectors which traditionally find it difficult to access finance.[2] The EIB also launched the European Investment Fund, which invests in venture capital and growth funds that support innovative high-tech SMEs in their early and growth phases, as well as technology transfer and business incubators.

Other development banks are supporting SMEs and innovations, with several programmes and initiatives. For example, in 2015, the EBRD invested a total amount of 9.4 billion euros within the so-called Knowledge Economy Initiatives, with the aim of promoting innovation by supporting four target areas: innovation policy; information infrastructure; technological upgrading for industry; and financing for small innovative tech companies, including the Information and Communication

[2] For example, the InnovFin Energy Demo Project targets innovative first-of-a-kind commercial-scale demonstration projects to help companies to bridge the gap from demonstration to commercialization. Similarly, the InnovFin Infectious Diseases Finance Facility provides financial products for R&D-oriented companies to develop new innovative vaccines, drugs, medical and diagnostic devices or novel research infrastructures. Since 2014, the InnovFin programme has financed 87 projects mainly in ICT, Telecom & Media (17 percent), Life Science, Medical Technology, Pharma % Health Care (13 percent), Energy (13 percent), Metallurgy and Manufacturing and Process Industries (13 percent). Among the institutions and companies supported, there are: CERN (CH), Novabase (PT), Welltec (DN) and AW-Energy (FL).

Technology (ICT) industry. Similarly, KfW supports innovative start-up entrepreneurs, the self-employed and SMEs with a broad spectrum of financing and advisory services with the aim of creating a funding environment for innovators. Among the financial instruments used by KfW to support SMEs, the most relevant are the “ERP innovation programme”, which provides long-term funding for the development of new products, product processes and services, and the “ERP Start-up Fund”, which is specifically involved in the young companies’ foundation phase. KfW also indirectly invest in young companies through the “ERP Venture Capital Fund Investments”, that is, the provision of funds to venture capital in order to leverage private capital for innovative start-ups. The websites, annual relations and financial statements of other development banks highlight a fast-growing involvement in financing innovation, from large-scale research to small programmes, in a number of areas including the medical diagnostics, dermatology, materials processing, gas sensors, combustion process control and home security night-vision sectors.

The role of development financial institutions in financing innovation is therefore relevant and growing over time. In this light, a proper empirical evaluation of the impact of their funding activity on firms’ innovation may add knowledge about the features of such institutions and contribute to the more general and growing debate on contemporary state-owned enterprises in Europe (Bernier et al. 2020; Karolyi and Liao 2017; Musacchio and Lazzarini 2014; Bruton et al. 2015; Clò et al. 2017; Cuervo-Cazurra et al. 2014; Benassi and Landoni 2019).

3. Data and variables

Since our analysis is focused on European development financial institutions (DFIs), we start our empirical research by defining a taxonomy of these institutions. In line with Frigerio and Vandone (2020), we start the identification and mapping of European DFIs by recurring to the banks’ classification available within the Orbis Bank Focus database,[3] produced by Bureau van Dijk (BvD), a Moody's Analytics company specialized in collecting private company data and business information. In particular, we find that most of the European DFIs are classified as *Specialized governmental credit institutions* or *Multi-lateral governmental banks*. Second, we also select an additional list of DFIs by directly referring to the firms' description and ownership information available within both the Orbis Bank Focus and the Orbis databases.[4] We then refine the initial selection of European DFIs through manual inspection and a general review of annual reports and publicly available information. The final list includes 132 entities, which to the best of our knowledge represent the population of DFIs in Europe.[5] Moreover, according to ownership data available in Orbis, we also consider as development financial institutions all the additional entities that result as direct or (second-order) indirect subsidiaries that are more than 50 percent owned by the main DFIs identified above. For the purposes of our empirical analysis, deals (transactions) with development financial institutions as acquirers (investors) are compared with a selected sample of deals without the participation of development financial institutions.

Relevant deals for our study were identified by using the Zephyr database (BvD), which reports information on worldwide corporate transactions, including mergers and acquisitions (M&As), initial public offerings (IPOs), venture capital and private equity deals. To build our data set, we select from Zephyr the deals whose financial method is classified by BvD either as Private Equity or Venture

[3] Orbis Bank Focus is a bank-level global data set reporting yearly data and information on banks, including their balance-sheet, account and legal status, corporate governance and organization and ownership structure.

[4] While Orbis Bank Focus is specifically dedicated to banks, the Orbis database includes financial firms that are not classified as banks but can nevertheless be included in the taxonomy of development financial institutions.

[5] We narrow our analysis on European financial institutions, as DFIs have been particularly increasing their relevance in this geographical area compared to other areas, such as the United States, where the private venture capital market is more developed.

Capital.[6] Deals classified as majority stakes acquisitions or mergers are excluded from our analysis as they are not typically oriented at fostering innovation in start-up companies. Deals are selected for each year within the 2008–2017 period.

For the selected deals, we also extract the following main information: the year of the deal; the deal value; the deal type; the number of acquirers per deal; the names of the target and of the acquirer companies; and their respective identification numbers (IDs). These IDs are then used to extract from the Orbis dataset additional information on the acquirers and targets of the selected deals.

Concerning the acquirer, we extracted information on their geographical location. This allowed us to restrict our analysis to deals where the acquirer/investor is headquartered in Europe and, consequently, to consider a benchmark sample that is geographically consistent with our choice to focus on European DFIs. Moreover, the matching between BvD Zephyr and Orbis data sets based on the acquirer IDs permits us to identify exactly those transactions where at least one development financial institution materializes among the investors.

[6] To be precise, we also select angel investment, development capital and corporate venturing, although these features mostly overlap with at least one of the two main financial methods selected (private equity and venture capital). Indeed, according to the BvD's Zephyr glossary, a deal's financial method is classified as a: i) *Private Equity* when the deal contains an element of private equity activity on the Acquirer's side of the deal whether this is through funding or through an MBO, an MBI or an IBO; ii) *Venture Capital* when the deal contains an element of Venture Capital activity on the Acquirer's side of the deal via a Development Capital deal; iii) *Development capital* when a Venture Capital/Private Equity firm takes a minority stake in the Target company, for investment purposes; iv) *Angel Investment* when a 'business angel' invests in a firm that is often a start-up or developing company, and a business angel is a financial institute that invests in companies in much the same way that venture capital companies do; *Corporate Venturing* when a non-Venture Capital/Private Equity company joins a round of Development Capital financing, usually jointly with a Venture Capital/Private Equity company. This can also be used if one of the Venture Capital/Private Equity firms is owned by a non-financial company.

Concerning the target company, we extracted information on their geographical location and economic activity (NACE rev.2), plus a number of other characteristics and financial variables that have been identified to be relevant in explaining the firm's capacity to innovate: year of incorporation; tangible and intangible assets; operating revenues; and whether the firm is listed on a stock market. Finally, for each target company, we extract information on its patenting activity (year of patenting, patent office, abstract of the patent, year of granting), since 1980, as reported in the ORBIS database. Indeed, Bureau Van Dijk has extended the OECD HAN database (Harmonised Applicants' Names) (Thoma et al. 2010) and provides a reliable matching of patent assignee names (and the corresponding publication numbers) with ORBIS firms. Data on the target companies are collected up to 2018 in order to extend available information that is necessary to analyse the post-deal performances in terms of innovation activity.

After combining the information collected from the data sources described above, we restricted our sample to those years with non-missing information on the variables of our main interest, thus creating an unbalanced panel data set comprising 80,713 firm-year observations referring to 12,437 deals. The number of deals shows a fairly uniform yearly distribution during the considered period. On average, our sample is composed of 1,327 deals per year (not considering 2017, since deals data do not refer to the whole year). A lower than average amount of deals is registered in 2009, that is, after the financial crisis, while a higher than average number of deals is registered in the years 2014 and 2015.

Deals can be analysed according to the acquirer type. In particular, we distinguish deals backed by at least a DFI (*DFI deals*) from deals where no DFI appears among the acquirers (*non-DFI deals*). Out of these 12,437 deals, 10 percent include at least one DFI among the acquirers (1,242 deals). The yearly distribution of deals per type of acquirer is quite uniform over the considered period. Only in 2008 is the share of deals counting a DFI significantly lower than average (5 percent), while in 2013 and 2017, it represents up to 13 percent of the deals (Table 1).

[TABLE 1 AROUND HERE]

Further information emerges when we analyse the deals including at least one DFI among the acquirers (Table 2). It is interesting to observe that a DFI rarely carries out a financial transaction without any partnership. Only 270 out of the 1,242 selected deals backed by a DFI include just a single DFI on the acquirer side (*only-DFI* deals). In 78 percent of the DFI-backed deals, the DFI builds a partnership with other non-DFI financial institutions in order to provide financial support to the target companies [*mixed (DFI+non-DFI)* deals]. We shall take into account this relevant aspect in our empirical strategy.

[TABLE 2 AROUND HERE]

Looking at the full sample, 31 percent of the 80,713 firm-year observations refer to a pre-deal period. Sixty-three percent of the sample refer to observations in the year of the deal or after the deal, when the financial transaction is backed only by non-DFIs (*Post-deal non-DFI*). Six percent of the sample is composed of post-deal observations where the deal includes at least one DFI among its acquirers (*Post-deal DFI*).

[TABLE 3 AROUND HERE]

The distribution of equity deals by activity class of the target firm (Table 4) reveals that DFIs tend to shift financial resources toward *High-tech knowledge-intensive services [e.g. Scientific Research and Development (NACE code 72)]*, *High-technology Manufacturing [e.g. Manufacture of Computer, Electronic and Optical Products (NACE code 26)]* and *Knowledge-intensive market (*and *financial) services,* at the expense of *Less knowledge-intensive market services [e.g. Retail Trade (NACE codes 46-47)]*, *Low-technology manufacturing* and *Other less knowledge-intensive services*. The focus on sectors that are supposed to be important sources of innovation and productivity growth serves as initial evidence of the willingness of DFIs to support innovation through the participation in the equity deals analysed in this research.

[TABLE 4 AROUND HERE]

Having described the relevance of DFIs within our sample of deals oriented at fostering innovation in start-up companies, we are mainly interested in explaining the effect of the financial support of DFIs on the innovative activity of the target companies. To this aim, we used the number of patent applications filed by each target company as a proxy of their innovation. Patent applications are collected regularly, and they are publicly available documents which measure a tangible outcome of the R&D process and allow for international comparability (Griliches, 1990). To improve the patents' capacity to be a good proxy of the genuine firm's innovation, we take into consideration only patents filed in the main patent offices (USPTO, EPO, JPO and WIPO). These patent offices typically ensure higher quality, stringency and transparency in the evaluation procedure, and they grant a wider geographical intellectual property (IP) protection in the most relevant markets (Clò et al. 2020).

Figure1 shows the yearly stock of patents filed (on average) by a target company in a time window from three years before to five years after a deal took place, and by distinguishing per type of acquirer. The patent stock shows stronger increases in post-deal years when the deal is backed by a DFI. However, the average stock in years -1 and 0 reveals that target firms of deals backed by DFI tend to have an already higher stock of patents than other target firms in the deal year. This suggests that our empirical regressions will need to control for these different starting points.

[FIGURE 1 AROUND HERE]

We also include in our analysis a set of variables recognized as relevant to explain the firm's innovative activity at the firm level. From accounting data, we look at the amount of investment in tangible assets and operating revenues, which can be considered a good proxy for the firm size and profitability. We also look at the level of investments in intangible assets that can be considered an imperfect, but still reliable, proxy of R&D investment when data on R&D expenses are not available (Leoncini et al 2018; Marin 2014). We also consider the firm's age and whether it is listed on the stock market.

Table 5 reports descriptive statistics for these characteristics among the target companies, differentiating them per type of acquirer. Compared to those backed by DFIs, target companies financed by non-DFIs show higher operating revenues, tangible and intangible assets. The share of listed companies is low in both cases (below 7 percent). This can be primarily explained by their young age, with DFI-backed target companies being on average two years younger than non-DFI backed companies. Finally, the DFI targets show on average a slightly higher amount of patents applications compared to non-DFI targets.

[TABLE 5 AROUND HERE]

4. Estimation strategy and results

We are interested in examining whether deals involving development financial institutions affect the innovation activity of target firms more than deals with similar characteristics that are not backed by development banks. Our approach is aimed at addressing the general question about the DFIs' capacity to support innovation compared to other investors. Section 4.1 describes the empirical strategy adopted to address these questions, while Section 4.2 presents our main results on the relationship between DFI financial support and firm patenting activity. In the same section, we analyse how this relation varies when DFIs enter a deal jointly with non-DFIs.

4.1 Model specification

We rely on a negative binomial specification model to study the impact of financial support granted by DFIs and non-DFIs on the target companies' innovative capacity. The choice of this model depends on two main issues. First, our dependent variable – the number of patent applications – is a count variable containing only positive and integer values, thus making it inappropriate to adopt an ordinary least squares (OLS) estimator. In this case, the standard procedure would be to adopt a

Poisson regression model (Hausman et al. 1984). However, our data show overdispersion compared to the Poisson distribution ($E[Y] = var[Y] = \vartheta$), which assumes the sample variance of the patent variables being equal to the sample mean. This makes it advisable to adopt a negative binomial regression, where the Poisson regression model is generalized by introducing an unobserved heterogeneity term which is independent on the vector of regressors X_i (Greene 1997).

Various papers use the negative binomial model for an unbalanced panel to estimate the determinants of innovative activities (Allison and Waterman 2002; Furman and Stern 2011; Castelnovo et al. 2018).[7] The first specification of the negative binomial regression model with standard errors being robust to heteroscedasticity is given by:

$$E\left[PAT_{i,t}\right] = exp(\alpha + \beta PostDeal_{i,t} + X'_{i,t}\gamma + Z'_{i}\delta + \theta Y_t + \varepsilon_i) \quad (1)$$

where the dependent variable is the expected number of $PAT_{i,t}$, the number of patents filed by target company i in year *t*. $PostDeal_{i,t}$ is a dichotomy variable taking the value of 1 in the year of the deal and in the following years, while taking value 0 in the pre-deal years. With this first model specification, we want to understand whether the firm's capital increase following the financial support granted by a financial institute, either DFI or non-DFI, is associated with an increase in the firm's innovative activity. To obtain unbiased estimates, we control for potential confounding factors. The vector $X_{i,t}$ includes the set of control variables described in Section 3. As for firm-level controls, the size of the company is proxied by its operating revenues, tangible assets measure the firm's capital expenditures, and intangible assets are used as a proxy for internal R&D effort, since data on R&D expenditures are mainly unavailable. All these financial characteristics are log-transformed for estimation purposes. We also considered whether the firm is listed on a stock exchange and include the age of the firm among the explanatory variables. We also include among the explanatory variables

[7] In unreported tests, we also use the Poisson regression model, and we find that the main results are confirmed and do not depend on the adopted model specification. Tables are available upon request.

the GDP annual growth rate and the inflation annual growth rate measured by the consumer price index (CPI) referring to the country where the target company is located. Explanatory variables include also the value of the deal, which is reported only in the year of the deal. Time, geographical and sector fixed effects are also included: the vector Z_i controls for time-invariant differences in patenting activities across geographical areas and sectors,[8] while year fixed-effects Y_t capture time-dependent common shocks, including macroeconomic exogenous shocks.

Then, we extended the baseline model (1) by differentiating the post-deal data according to the type of acquirer, whether a DFI appears among the agents providing financial support to the target company through the deal (equation 2). This allowed us to assess whether the presence of a DFI in the deal is associated with a change in the target company's innovative capacity, both compared to the pre-deal period and to the deals backed only by non-DFIs.

$$E\left[PAT_{i,t}\right] = exp(\alpha + \beta DFI_{i,t} + \varphi nonDFI_{i,t} + X'_{i,t}\gamma + Z'_i\delta + \theta Y_t + \varepsilon_i) \quad (2)$$

The variable $DFI_{i,t}$ is used to identify target companies that have been financed at least by a DFI. It is a dichotomy variable taking the value 1 in the post-deal years, but only when a DFI appears among the financing institutions involved in the deal. This variable takes the value 0 in the years before the deal and whenever a deal is not backed by a DFI. Similarly, $nonDFI_{i,t}$ refers to those deals involving only non-DFIs. It takes a value of zero in the years before the deal and whenever a DFI is involved in a deal, while it takes a value of 1 in the year of the deal and in the following years, but only when non-DFIs are involved in the deal.

We finally extend the model in order to distinguish deals where DFIs are the only financing institutions from deals where DFIs join non-DFIs in a partnership:

[8] Target companies are classified into eight geographical areas (Africa, Eastern Europe, Western Europe, Far East and Central Asia, Middle East, North America, Central & South America and Oceania), while the NACE rev. 2 (2 digit) classification is considered to identify the companies' economic sector of activity.

$$E[PAT_{i,t}] = exp(\alpha + \beta onlyDFI_{i,t} + \varphi nonDFI_{i,t} + \omega mixedDFI_{i,t} + X'_{i,t}\gamma + Z'_i\delta + \theta Y_t + \varepsilon_i) \quad (3)$$

The variable $onlyDFI_{i,t}$ takes a value of 1 in the post-deal years, but only when DFIs participate in the deal on the acquirer side. Conversely, the variable $mixedDFI_{i,t}$ takes a value of 1 in the post-deal years, when both DFIs and non-DFIs participate jointly in a deal. Both variables equal zero in the pre-deal period. As before, the variable $nonDFI_{i,t}$ identifies those target companies that have been financed only by non-DFIs, and it takes a value of 1 in the post-deal period.

The negative binomial regression model is appropriate when the dependent variable takes non-negative and integer values and is characterized by a positive-skewed distribution with a long right tail. Moreover, this model is robust to a number of misspecifications such as overdispersion, the presence of an excessive number of zeros. Nevertheless, we have conducted a variety of robustness checks to exclude the possibility of our main results being dependent on the chosen empirical strategy. Specifically, we show that our main results are robust to alternative and more stringent specifications of the regression model.

4.2 Results and discussion

Table 6 contains the results from model 1 above. Column 1 reports the baseline knowledge production function without considering any deal. Results show that the number of patents is positively and significantly associated with the size of the firm (measured by the log of operating revenues and by the log of tangible assets), the intensity of R&D internal effort (proxied by the log of intangible assets) and with the fact of being listed on a stock market. Listed companies manage to attract a larger amount of private equity and become more financially accountable. Both phenomena contribute to explaining this result. The age of the firm is negatively correlated with the patenting activity, suggesting that younger firms and start-ups are more oriented towards innovative activities.

In Column 2 of Table 6, we explicitly take into account the deals' events involving the target companies. The positive and statistically significant coefficient of the *PostDeal* variable indicates that firms' patenting activity experiences an increase in the post-deal period. This suggests that the financial support provided by financial institutions through the deal contributes to improving firm-level innovation performance.

[TABLE 6 AROUND HERE]

In Table 7, we report the main results of our analysis. In Column 1, we test our research question relating to the differential role of DFIs on firm-level innovation performance when controlling for major potential confounding factors (equation 2). Notably, the *PostDeal* variable is decomposed into two different explanatory variables. $DFI_{i,t}$ identifies the post-deal years for those companies that have been targeted in a deal where a DFI was present among the institutions providing financial support. Similarly, the variable $nonDFI_{i,t}$ refers to the post-deal years for those companies that have been targeted only by non-DFIs. Both coefficients of these explanatory variables are positive and statistically significant, with the $DFI_{i,t}$ coefficient being higher than the $nonDFI_{i,t}$ coefficient. This points to the fact that the level of patenting activities is higher for those companies that have been financially backed by at least one DFI. The finding that the number of patents is on average higher when DFIs are among the institutions providing financial support to the target companies represent initial novel evidence on the innovative-oriented mission driving the financial activity of DFIs. This is widely stated in the DFIs' statutes, but, to the best of our knowledge, was not documented through the empirical analysis.

It is worth to highlight that this finding – the positive correlation between the DFI support and the financed company' innovation – is not sufficient *per se* to infer a causal relationship between the DFI's financial activity on the supported firms' innovative performance. Firms might increase their patenting activity mainly because they are backed by DFIs, or – conversely – DFIs might just be good at targeting better companies with a higher innovation potential. In this latter case, the DFI would not play any marginally incremental role in supporting firm innovation. We can observe that both potential interpretations of the positive correlation among DFIs and target companies' innovation are consistent and do not disprove the main argument on the DFIs' orientation towards the financial support of innovation. We will return to these concepts in more detail in the robustness checks.

In Column 2 of Table 7, we further disentangle the DFIs' role by distinguishing those deals involving on the acquirer side only the DFIs ($onlyDFI_{i,t}$) from those deals where target companies received financial support from both DFIs and non-DFIs ($mixedDFI_{i,t}$). Both coefficients are positive and statistically significant, with the latter being higher than the former, and with the $onlyDFI_{i,t}$ coefficient being higher than the $nonDFI_{i,t}$ coefficient. This finding suggests that partnerships among DFIs and non-DFIs are associated with the best performance in target companies in terms of patent activity. This finding is not driven by the size of the financial support provided to the target companies – which is already captured by the value of the deal – which is explicitly accounted for among the control variables. This result might be explained in light of the positive synergies resulting from the collaboration among two types of financial institutions which show different, and potentially complementing and reinforcing, competences. On one side, DFIs' strategies can be characterized by a long-term horizon, which is compatible with the support of innovative activities with uncertain and time-deferred returns. This is consistent with the "patient capital" opportunity that has been associated with financial institutions controlled by the government (Hoskisson et al. 2002).[9] On the other side, private financial institutions, such as venture capitals, can benefit from higher internal skills and lower agency costs, resulting in a better capacity to spur innovation (Bottazzi et al. 2008) compared to government funds which might have lower monitoring

[9] This opposes the short-termism critique that can affect private companies re-directing resources from R&D-oriented activities to more conventional short-term ones (Porter 1992; Stein 1988) Evidence of the short-termism has been found when looking at private enterprises listed on the stock market (Ferreira et al. 2013), especially when there is participation from speculating investors (Bushee 1998, 2001).

capacities (Cumming and Johan 2014). Interestingly, our finding is consistent with various studies that have analysed the role of private and government-backed venture capitals, and their interplay, in improving firms' performance and innovation. In particular, Cumming and colleagues (2017) analysed a European dataset and found that mixed investments by private and government-backed venture capitals increase the likelihood of positive exits compared to firms financially supported only by private venture capitals. Grilli and Murtinu (2014) argue that government involvement in the venture capital market is effective in supporting high-tech entrepreneurial firms only when developed in partnership with independent venture capitals. Brander et al. (2014) find that enterprises co-founded by private and public funds obtain more investment and show a higher probability of successful exit. Bertoni and Tykvová (2015) analysed the patents registered by 665 European biotechnology start-ups and young companies, finding that innovation increases when DFIs and private venture privates co-invest, compared to firms with only one type of investor.

[TABLE 7 AROUND HERE]

5. Robustness checks

In this section, we present a variety of robustness checks to exclude the possibility of our main results being dependent on the chosen empirical strategy. Specifically, we show that the results are robust to alternative specifications of the chosen estimator, when different explanatory and dependent variables are considered and with a different sample being analysed. In particular, more stringent specifications of the model are going to be presented to correct for some potential biases that might affect the main results previously presented.

5.1 Propensity Score Matching Procedure

First, the association between deals involving DFIs and the level of patent activity could be due to endogenous selection of firms based on their fundamental characteristics. To address this potential selection bias, we match the deals with DFI participation (treatment sample) with deals having similar characteristics but without DFIs (control sample). Specifically, we firstly form a sample of deals with targets in the same country and industries as for targets in the treatment sample. We then estimate the probability of having a DFI in a deal conditional on loan-level characteristics in the deal year (i.e. operating revenues, tangible and intangible assets, age, a dummy variable for publicly listed companies) and also on year dummies and on the pre-sample mean of patents applied by the target company. For each deal in the treatment sample, we select up to five deals in the control sample (i.e. without DFI participation) using the closest propensity scores obtained from the corresponding probit estimation.

Figure 2 shows the good quality of the matching procedure adopted. Indeed, differences in the propensity score distribution between the treated and control groups significantly decrease after the matching.

[FIGURE 2 AROUND HERE]

Table 8 reports the estimates when rerunning our regressions within the matched sample. The results corroborate our baseline findings, as the effect of DFI participation remains statistically significant at the 1 percent level, with very similar magnitudes as in the baseline regressions.

[TABLE 8 AROUND HERE]

5.2 Other robustness checks

The second set of robustness checks pertains to the nature of the dependent variable. As shown, the patent counting variable presents a positive-skewed distribution with a long right tail with a high share of zeros (firms not filing any patent in various years). In order to verify whether our results are robust to the high number of zeroes, we ran a zero-inflated negative binomial (ZINB) which is robust to zero outcomes as well as over-dispersion of the count data (Hausman et al. 1984, Mullahey 1986, Greene 1997, Cameron and Trivedi 2005). The ZINB regression model fits a logit model which predicts the probability of not patenting into a negative binomial model.

Results reported in Table 9 are consistent with our previous findings. Patenting activity is positively associated with the financial support provided by the deal, and this is stronger when DFIs are present in the deal. Moreover, the results of the logit regression suggest that the probability of not patenting is lower after a deal takes place, and it is lowest when DFIs and non-DFIs jointly participate in the deal. It is possible to show that these findings are widely confirmed when a hurdle negative binomial regression model is used as alternative technique to overcome the problem of overdispersion and an excess of zeros. While the ZINB permits the decision not to patent in a mixture of negative binomial and logit models, the Hurdle negative binomial keeps the decision to patent separated from the process generating the positive outcomes.[10]

[TABLE 9 AROUND HERE]

Another criticism might concern the choice of the explanatory variables. Notably, innovation and patenting take time to materialize. Thus, we run again our main regression considering a timespan among the explanatory variables and the dependent variable. In Columns 1 and 2 of Table 10, the main control variables are one-year lagged compared to the patents' year of observation, while in Columns 3 and 4, both values at time t and t-1 are considered. The results are consistent with previous findings.

[TABLE 10 AROUND HERE]

The low within variation of our main explanatory variable (being targeted by a DFI or by a non-DFI) and the unobserved heterogeneity might affect our estimates. To address this issue, we included among the explanatory variables the pre-sample mean of patents applied by the target company. This pre-sample mean captures the firm's patent capability prior to our considered period and proxies for

[10] Results of the Hurdle negative binomial are not reported and are available upon request.

the unobserved difference among firms in their ability to patent, allowing us to control for possibly correlated, time-invariant heterogeneity (Blundell et al. 2002). As expected, the patent pre-sample mean shows a positive and significant coefficient. More importantly, even after capturing the firm-specific effect through the pre-sample mean, our main results are confirmed. Being targeted by a DFI is positively associated with the firm's capability to patent, and the size of this relation is higher compared to firms targeted by non-DFIs. Moreover, firms targeted by a joint partnership among DFIs and non-DFIs perform better (in terms of patents) than firms targeted by only non-DFIs, but not better than firms targeted by only DFIs.

[TABLE 11 AROUND HERE]

6. Conclusions

In our paper, we analyse the portfolio of equity deals made by development banks in financing innovation, and we investigate the impact of these deals in explaining the innovative activity of the target companies. Innovation is proxied by the total number of patent applications filed every year by each target enterprise company composing our sample; after mapping all development financial institutions headquartered in Europe, we use Zephyr to identify deals and Orbis to extract balance sheet information on the acquirers and targets, as well as the patenting activity for each target.

Our results are threefold. First, empirical findings suggest that financial support provided by financial institutions through the deal contributes to improving firm-level innovation performance. Second, the number of patents is on average higher when DFIs are among the institutions providing financial support to the target companies. Third, partnerships among DFIs and other (non-development) financial institutions are associated with the best performance in target companies in terms of patent activity.

The role of DFIs in providing financial support through equity deals represents novel evidence on the innovative-oriented mission driving their financial activity. Indeed, although the innovative-oriented mission is widely stated in their statutes, to the best of our knowledge it has never been documented through empirical analysis. These results are particularly relevant in light of the increasing role development financial institutions have been called upon to play in the aftermath of the economic and financial global crisis by European policy makers to share the management of EU financial instruments, to catalyse long-term private finance and to be instrumental in technology promotion and innovation, as well as in supporting structural changes in economies such as, among others, renewable energy, resource efficiency, food security and climate change.

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Table 1. Deals yearly distribution. Type of acquirer.

	Number of deals without DFIs (non-DFI deals)	Number of deals with at least one DFI (DFI deals)	Total
2008	1,141	57	1,198
2009	741	80	821
2010	1,043	100	1,143
2011	1,089	130	1,219
2012	1,111	148	1,259
2013	1,209	181	1,390
2014	1,561	162	1,723
2015	1,582	172	1,754
2016	1,292	148	1,440
2017	426	64	490
Total	11,195	1,242	12,437

Table 2. Number of deals. Type of acquirer.

	Deal	
	Number	Percentage (%)
Non-DFI	11,195	90.0
DFI, of which:	1,242	10.0
only-DFI	*270*	*2.2*
mixed (DFI + non-DFI)	*972*	*7.8*

Table 3. Pre-deal and post-deal observations. Type of acquirer.

	Freq.	Percentage (%)
Pre-deal	25,041	31.0
Post-deal non-DFI	50,555	62.6
Post-deal DFI, of which:	5,117	6.3
Post-deal - only-DFI	*1,336*	*1.7*
Post-deal - mixed	*3,781*	*4.7*
Total	80,713	100.0

Table 4. Deals distribution by activity class of the target firm.

	Observations		Percentages (%)	
Activity classes	Non-DFI Deals	DFI Deals	DFI Deals	Non-DFI Deals
High-tech knowledge-intensive services	3,018	432	27.0	34.8
Less knowledge-intensive market services	2,385	157	21.3	12.6
Knowledge-intensive market services	1,312	154	11.7	12.4
Other knowledge-intensive services	802	75	7.2	6.0
Knowledge-intensive financial services	753	89	6.7	7.2
Low-technology manufacturing	688	56	6.1	4.5
Medium-high technology manufacturing	642	74	5.7	6.0
Medium-low technology manufacturing	464	49	4.1	3.9
High-technology manufacturing	448	105	4.0	8.5
Construction	270	20	2.4	1.6
Electricity, Gas, Steam and Air Conditioning Supply	159	13	1.4	1.0
Other less knowledge-intensive services	109	5	1.0	0.4
Other classes	145	13	1.3	1.0
Total	11,195	1,242	100.0	100.0

Following Eurostat classification, manufacturing industries are aggregated according to technological intensity (R&D expenditure/value added) and based on NACE Rev.2 at 2-digit level. Similarly, services are mainly aggregated into knowledge-intensive and less knowledge-intensive services based on the share of tertiary educated persons at the NACE 2-digit level.

Table 5. Target values per type of acquirer.

	Operating Revenues (th. €)		Intangible Assets (th. €)		Tangible Assets (th. €)	
	Mean	SD	Mean	SD	Mean	SD
non-DFI targets	66,846.1	553,287.1	12,070.0	261,522.2	16,626.1	320,487.8
DFI targets	98,616.9	1,110,299.0	30,789.7	782,809.7	60,608.0	755,371.8
	Listed (%)		Age		Patent Applications	
	Mean	SD	Mean	SD	Mean	SD
non-DFI targets	6.2	24.1	15.0	17.5	0.6	8.5
DFI targets	6.7	24.9	12.9	14.9	1.3	13.4

Table 6. Knowledge production function estimates: the role of financial support through a deal.

	(1)	(2)
PostDeal		0.746***
		(0.066)
Tangible Assets (ln)	0.121***	0.115***
	(0.015)	(0.015)
Intangible Assets (ln)	0.120***	0.120***
	(0.009)	(0.009)
Operating Revenues (ln)	-0.187***	-0.173***
	(0.039)	(0.040)
Age	1.704***	1.651***
	(0.121)	(0.131)
Listed	-0.016	-0.007
	(0.015)	(0.015)
Deal Value	0.435***	0.275***
	(0.132)	(0.103)
Constant	-10.488***	-11.153***
	(0.826)	(0.808)
Observations	80,713	80,713
Year, Area, Sector Fixed effects	YES	YES
Country GDP & inflation annual growth rate	YES	YES
R2	0.093	0.096

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7. Knowledge production function estimates: the role of DFIs and partnership among DFIs and non-DFIs.

	(1)	(2)
non-DFI	0.673***	0.675***
	(0.067)	(0.066)
DFI	1.284***	
	(0.092)	
only-DFI		0.814***
		(0.216)
mixed-DFIs		1.412***
		(0.094)
Observations	80,713	80,713
Year, Area, Sector Fixed effects	YES	YES
R2	0.097	0.097

*** p<0.01, ** p<0.05, * p<0.1; robust standard errors are reported in parentheses. The following explanatory variables are included in the regressions, although their coefficients have not been reported for space reasons: operating revenues; tangible and intangible assets; age of the firm; whether it is listed; country GDP; and inflation annual growth rate. The sign of their coefficient is consistent with the results presented in Table 6.

Table 8. Propensity score matching.

	(1)	(2)
non-DFI	0.647***	0.650***
	(0.068)	(0.068)
DFI	1.110***	
	(0.094)	
only-DFI		0.792***
		(0.210)
mixed-DFIs		1.194***
		(0.096)
Observations	34,776	34,776
Year, Area, Sector fixed effects	YES	YES
R2	0.084	0.084

*** $p<0.01$, ** $p<0.05$, * $p<0.1$; robust standard errors are reported in parentheses. The following explanatory variables are included in the regressions, although their coefficients have not been reported for space reasons: operating revenues; tangible and intangible assets; age of the firm; whether it is listed; country GDP; and inflation annual growth rate. The sign of their coefficient is consistent with the results presented in Table 6.

Table 9. The role of DFIs and partnership among DFI and non-DFI – ZINB regression.

	(1)	(2)	(3)	(4)
	Negative binomial	Inflate	Negative binomial	inflate
non-DFI	0.254***	-0.530***	0.253***	-0.529***
	(0.060)	(0.048)	(0.060)	(0.047)
DFI	0.414***	-1.125***		
	(0.089)	(0.077)		
only-DFI			0.651**	-0.179
			(0.273)	(0.155)
mixed-DFIs			0.374***	-1.411***
			(0.085)	(0.083)
Observations	80,713	80,713	80,713	80,713
Year, Area, Sector Fixed effects	YES	YES	YES	YES

*** $p<0.01$, ** $p<0.05$, * $p<0.1$; robust standard errors are reported in parentheses. The following explanatory variables are included in the regressions, although their coefficients have not been reported for space reasons: operating revenues; tangible and intangible assets; age of the firm; whether it is listed; country GDP; and inflation annual growth rate.

Table 10. The role of DFIs and partnership among DFI and non-DFI: lagged control variables.

	(1)	(2)	(3)	(4)
non-DFI	0.653***	0.639***	0.656***	0.642***
	(0.074)	(0.073)	(0.074)	(0.072)
DFI	1.241***	1.295***		
	(0.098)	(0.101)		
only-DFI			0.725***	0.853***
			(0.212)	(0.226)
mixed-DFIs			1.382***	1.420***
			(0.101)	(0.103)
Observations	68,489	66,801	68,489	66,801
Year, Area, Sector Fixed effects	YES	YES	YES	YES
Control Variable at time t-1	x		x	
Control Variable at time t and t-1		x		x
R2	0.100	0.102	0.100	0.102

*** $p<0.01$, ** $p<0.05$, * $p<0.1$; robust standard errors are reported in parentheses. The following explanatory variables are included in the regressions, although their coefficients have not been reported for space reasons: operating revenues; tangible and intangible assets; age of the firm; whether it is listed; country GDP; and inflation annual growth rate.

Table 11. The role of DFIs and partnership among DFI and non-DFI: patent pre-sample mean.

	(1)	(2)
Pre-sample patents' mean	0.156***	0.156***
	(0.002)	(0.002)
non-DFI	0.366***	0.366***
	(0.060)	(0.060)
DFI	0.743***	
	(0.081)	
only-DFI		0.602***
		(0.161)
mixed-DFIs		0.784***
		(0.086)
Observations	80,713	80,713
Year, Area, Sector Fixed effects	YES	YES
R2	0.170	0.170

*** $p<0.01$, ** $p<0.05$, * $p<0.1$; robust standard errors are reported in parentheses. The following explanatory variables are included in the regressions, although their coefficients have not been reported for space reasons: operating revenues; tangible and intangible assets; age of the firm; whether it is listed; country GDP; and inflation annual growth rate.

Figure 1. Average patent stock per number of deal and type of acquirer.

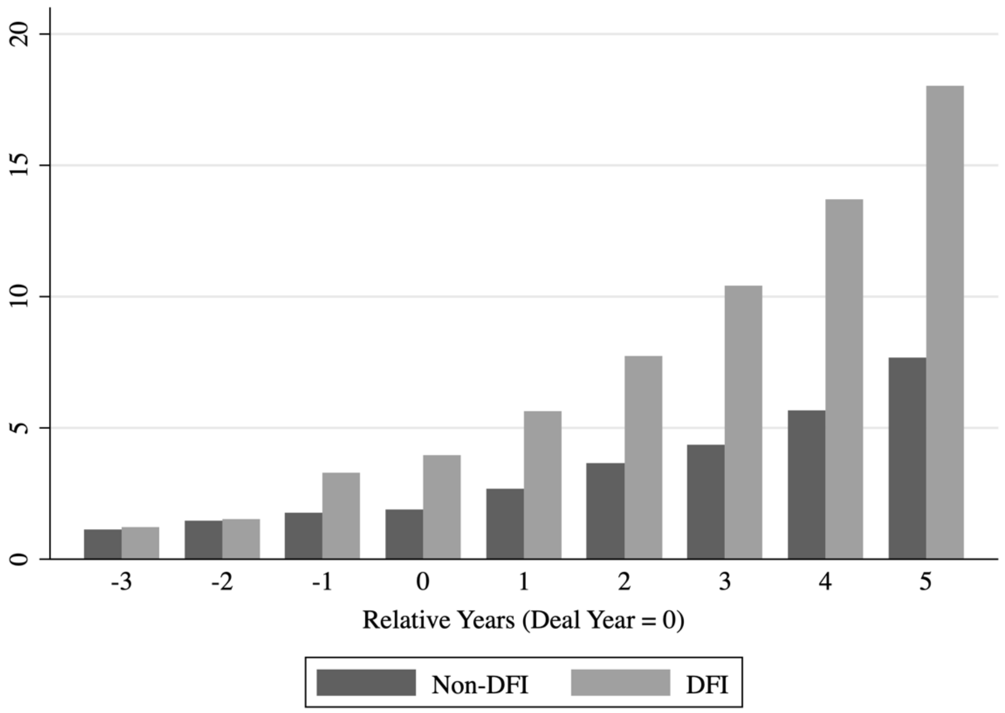

Figure 2. Propensity score distribution for treated and control groups before and after matching.