Financial Support to Innovation: The Role of European Development Financial Institutions

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Abstract

We analyse the role of European development financial institutions (DFIs) in supporting innovation by empirically investigating the impact of their participation as investors in equity deals on target firms' patenting activity. We build a unique international data set of deals and firm-level data in the years 2007–2019. Econometric results highlight the positive contribution of DFIs in mobilizing finance to support innovation, and the magnitude of this effect is amplified when DFIs act in partnership with other investors. This represents novel evidence on the innovative-oriented mission driving their activity. These new findings point to the recent role of DFIs in sharing the management of EU financial instruments, implementing programmes to strengthen the longer-term support of finance for enterprises, and boosting innovation and growth.

Keywords: development bank; development financial institution; state investment bank; equity deal; financing innovation; patents

JEL codes: G20; G21; O16; O38; L32; O19

1. Introduction

Development financial institutions (DFIs) – i.e. government-invested legal entities with an explicit policy mandate to carry out development or promotional activities[1] – have traditionally been part of the economic policy toolkit and the financial market landscape in Europe, playing a relevant role in mitigating market failures (De Aghion, 1999; Diamond, 1957). The 2008 crisis has further strengthened their function, since the European Commission and EU Member States have defined a common framework where the European Investment Bank and several national DFIs, also called national promotional banks, are sharing the management of EU financial instruments and implementing programmes to strengthen the longer-term availability of finance for enterprises and boost growth (European Commission, 2014; European Parliament, 2016).[2]

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[1] Definitions of development financial institutions, also referred to as development banks, state investment banks, promotional banks, include: 'public sector or government-invested legal entities with an explicit policy mandate to promote the socio-economic goals in a region, sector or specific market segment' (De Luna-Martinez and Vicente, 2012), 'institutions to promote and finance enterprise in the private sector' (Diamond, 1957); 'government-sponsored financial institutions concerned primarily with the provision of long-term capital to industry' (De Aghion, 1999); 'financial institutions that are primarily concerned with offering long-term capital finance to projects that are deemed to generate positive externalities and hence would be underfinanced by private creditors' (Yeyati et al., 2004); 'legal entities carrying out financial activities on a professional basis which are given a mandate by a member state or a member state's entity at central, regional or local level, to carry out development or promotional activities' (European Commission, 2015).

[2] According to theory, DFIs play a role in ensuring the functioning of existing markets by setting market failures, stimulating innovation paths and improving the institutional set up by supporting a response to new global challenges, such as environmental-friendly energy, food security, water sanitization (Bleda and Del Rio, 2013; D'Orazio and Lowenstein, 2020; Geddes and Schmidt, 2020; Geddes et al., 2018; Mazzuccato, 2013; Mazzuccato and Penna, 2016; Mazzuccato and Semieniuk, 2017, 2018; Mertens and Thiemann, 2018). DFIs typically fund projects with high risk and provide long-term "patient" capital to promote strategic investments (De Aghion, 1999; Diamond, 1957; Eslava and Freixas, 2021; Yeyati et al., 2007).

Such a financial support by DFIs aims at overcoming funding gaps stemming from a private financial sector being reluctant to provide funding if there are difficulties in evaluating the business, the innovation process, and therefore the expected returns and their distribution over time (and long period of time), or if there is a lack of guarantees and collaterals, which is typically the case of innovative activities (De Olloqui, 2013; Mertens and Thiemann, 2018; Musacchio et al., 2017). According to Mazzuccato and Semiemniuk (2017), "*while it is a common*

Several cases highlight the growing role of European DFIs in financing and stimulating technology innovation. The 2014 Investment Plan for Europe, aimed at facilitating access to finance innovation 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. The programme also includes thematic products addressing the specific financing needs of certain innovative sectors that traditionally find it difficult to access finance.[3] 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.[4]

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perception that it is private venture capital that funds start-ups, evidence shows that most high-growth innovative companies receive their early-stage high-risk finance from public sources". This is confirmed by Gaddy et al. (2017) and Geddes and Schmidt (2018).

[3] 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 per cent), Life Science, Medical Technology, Pharma % Health Care (13 per cent), Energy (13 per cent), Metallurgy and Manufacturing and Process Industries (13 per cent). Among the institutions and companies supported, there are: CERN (CH), Novabase (PT), Welltec (DN) and AW-Energy (FL).

[4] Other DFIs are supporting innovations, with several programmes and initiatives. For example, in 2015, the European Bank for Reconstruction and Development (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

Although some interesting recent papers focus on the increasing activity of DFIs in supporting innovative enterprises to realize their growth potential (starting with the seminal paper of Mazzuccato 2013, other relevant contributes are D'Orazio and Lowenstein, 2020; Geddes and Schmidt, 2020; Geddes et al., 2018; Mazzuccato and Semieniuk, 2017, 2018; Mertens and Thiemann, 2018), empirical studies on DFIs are still scant, they mainly concern case studies focusing on the lending activity of single institutions (Clifton et al., 2014, 2018; Robinson, 2009; Tuijnman, 2009), or on their political connections (Frigerio and Vandone, 2020; Lazzarini et al., 2015).

Within this context, the present paper aims at empirically evaluating whether EU DFIs effectively support innovation by estimating econometrically the impact of their participation as investors in equity deals. To address this question, we distinguish deals backed by DFIs from deals that are not backed by DFIs, and we analyse the financial characteristics of target firms and their patent applications, which we use to proxy innovation.

Specifically, we first extract from Zephyr, a database managed by Bureau Van Dijk (BvD), the entire set of equity deals[5] with at least one investor headquartered in Europe. Among them,

innovative tech companies, including the Information and Communication Technology (ICT) industry. Similarly, KfW supports innovative entrepreneurs with a broad spectrum of financing and advisory services, with the aim of creating a funding environment for innovators, especially in the renewable energy industry (D'Orazio and Lowenstein 2020; Geddes et al., 2018). Among the financial instruments used by KfW to support entrepreneurs, 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. The websites, annual relations and financial statements of other DFIs highlight a fast-growing involvement in financing innovation in a number of areas, from large-scale research to small programmes.

[5] In our framework, equity deals include both venture capital and private equity deals (see Section 2.2). These are alternative forms of financing, away from stock exchange markets, in which funds are typically raised from qualified investors with the aim of financing early-stage projects and growth strategies. Qualified investors typically include institutional investors – such as DFIs, insurance companies, university endowments and pension funds – and high-income and net worth individuals.

we first isolate deals participated by at least one DFI (*DFIbacked*). Then, within this category, we further distinguish *DFIonly* deals – backed exclusively by DFIs – and *DFIpartner* deals – backed by DFIs in partnership with other investors (hereinafter, other investors are also referred as non-DFIs). Since there is not a universally recognized and readily available classification of DFIs, a great effort is made to manually map all DFIs within the European Union using data and textual descriptions from Orbis Bank Focus and Orbis (Bureau Van Dijk), manual inspection, and other publicly available information. The list of DFIs is reported in Appendix A.

After matching data on equity deals with firm-level data, we end up with a longitudinal data set for the period 2007–2019, with 87,698 firm-year observations, referring to 13,695 deals, 1,081 of which count at least one European DFI among the investors (*DFIbacked*). In addition, we recur to propensity score matching (PSM) to select a subsample of target companies that are backed by DFIs and target companies that are not backed by any DFIs, whose differences in the pre-deal period (including their patenting activity and economic performance) are not statistically significant. This quasi-experimental design reduces the risk of our results being affected by a potential selection bias issue.

The empirical strategy involves several steps. First, we adopt a two-way fixed effects (TWFE) approach to compare the post-deal variation in the patenting activity between target companies that are backed by DFIs and target companies that are not backed by any DFIs. The TWFE estimator allows controlling for firm-specific and time-specific confounders, thus avoiding a potential bias deriving from the omission of unobservables. Secondly, we extend the traditional TWFE model by explicitly considering multiple timing in the treatment, that is the variation of the year when equity deals take place. Through a panel event study approach, we first estimate a dynamic treatment effect which highlights its temporal dimension (e.g. whether it is increasing or decreasing in time) and allows to test for the parallel trend assumption.

Finally, building on Deshpande and Li (2019) and Fadlon and Nielsen (2021), we develop a staggered diff-in-diff design, which allows to assess the impact of the equity deals on the firms' patenting activity by fully exploiting the heterogeneity in the time of the treatment. Firms receiving financial support in year *t* through each one of the above-mentioned deal types (*DFIonly* deals, *DFIpartner* deals, and deals with no DFIs on board) are compared to other firms that have received financial support through the same type of deal in a year outside a [*t-3; t+3*] time window. The fact that both treated and control groups are composed exclusively by firms selected from the same type of deal further ensures our results to be robust to potential biases deriving from the non-random assignment of the treatment.

A battery of tests confirms that our results are robust to alternative specifications of the chosen estimator.

Econometric results highlight the positive contribution of development financial institutions in supporting innovation. The firms' patenting activity increases after they are targeted through an equity deal, and this increase is higher when DFIs act in partnerships with non-DFI investors, highlighting the positive synergies resulting from the collaboration among different types of investors that show different, and potentially complementing and reinforcing, competences. On the other hand, no statistically significant differences are found between deals backed only by DFIs (*DFIonly*) and deals that are not backed by any DFIs.

We also find that the incremental positive effect on innovation of DFI involvement is higher (i) when DFIs are located in high-institutional quality countries, since they are more likely to rely on internal stability, transparent monitoring and clear commitments towards long-term socially valuable goals, and (ii) for target firms in the high-tech and 'green' industries, since DFIs are more likely than private investors to support innovation in those sectors that generate positive effects on economic development and the society as a whole. These findings strengthen our underlying hypothesis on the relevant role played by DFIs in financing innovation through

their participation in equity deals. Indeed, if the positive effect of their participation was only due to the additional capital they provide with respect to other investors, there would be no reason to find stronger effects when the DFIs are established in countries with high-quality institutions and target firms operate in industries with positive social spillovers.

The remainder of the paper is organized as follows. Section 2 describes the data collected. Section 3 reports the main characteristics of the whole sample and of the subsample obtained using the propensity score matching approach. Section 4 presents the estimation strategy. Sections 5 and 6 present the results and a battery of robustness checks, respectively. Finally, Section 7 concludes.

2. The data

2.1 The list of European DFIs

We identified all the development financial institutions within the perimeter of the European Union, including the European Free Trade Association (EFTA) members (Norway, Switzerland, Iceland and Lichtenstein). In line with Frigerio and Vandone (2020), to identify the universe of European DFIs we first recur to the banks' classification available within the Orbis Bank Focus database,[6] 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*. 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.[7] We then refine the initial selection of European

[6] 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.

[7] 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.

DFIs through manual inspection and a general review of annual reports and publicly available information. The final list includes 106 entities, which to the best of our knowledge represent the population of DFIs in Europe. See Appendix A for the list of European DFIs and a description of their main characteristics and activities.

2.2 The equity deals and the characteristics of the target firms

We identified all deals for each year within the period 2007–2017 whose financial method is classified either as *private equity* or *venture capital* in the Zephyr database (BvD).[8] Deals are selected if at least one investor is headquartered in the European Union (including EFTA countries).

For the selected deals, we extract the following information: the year of the deal; the deal type; the number of investors per deal; the names of the target companies and their respective identification numbers (IDs).

These IDs are then used to extract from the Orbis data set additional information on the targets of the selected deals. Specifically, the matching between the BvD Zephyr and Orbis data sets based on the target IDs allows us to extract information on their geographical location and economic activity (NACE rev.2), plus a number of variables that have been identified as being relevant in explaining the firm's capacity to innovate: year of incorporation; tangible and intangible fixed assets; operating revenues; earning before interests and taxes (EBIT); and whether the firm is listed on a stock market.

[8] According to the BvD's Zephyr glossary, a deal's financial method is classified as: a *private equity* when the deal contains an element of private equity activity on the investors' side of the deal, whether this is through funding or through a management buy-out (MBO), a management buy-in (MBI) or an institutional buy-out (IBO); *venture capital* when the deal contains an element of venture capital activity on the investors' side of the deal via a development capital deal. See also footnote 4.

Data on the target companies are collected up to 2019 in order to extend available information to their post-deal performances in terms of innovation activity.

2.3 The patent activity

For each target company, we extract information on its patenting activity since 1980, as reported in the Orbis Intellectual Property database. Indeed, Bureau Van Dijk has extended the OECD HAN (Harmonised Applicants' Names) database (Thoma et al., 2010) and provides a reliable matching of patent assignee names (and the corresponding publication numbers) with Orbis firms.

Data on patenting activity are used as a proxy for the firm's innovation, in line with several empirical papers (among others, Acharya et al., 2014; Arqué-Castells, 2012; Benassi and Landoni, 2019; Bertoni and Tykvová, 2015; Bertoni et al., 2010; Clò et al., 2020; Faria and Barbosa, 2014; Geronikolaou and Papachristou, 2012; Hall and Lerner, 2010; Hirukawa and Ueda, 2011; Mann and Stager, 2007).

Indeed, patents are the most commonly used indicator to measure the effectiveness of investments devoted to innovation (Dodgson and Hinze, 2000). 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,[9] patents have several 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

[9] 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 reasons to increase economic barriers against market competitors; and (iv) a race to the patent behaviour 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; Kleinknecht et al., 2002; Langinier 2004).

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 (Hipp and Grupp, 2005; Kleinknecht et al., 2002). 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.

We restrict our analysis to patents filed in the world main patent offices – USPTO, EPO, JPO – which, on top of granting a wider geographical intellectual property protection in the most relevant markets, are acknowledged for presenting a rigorous and transparent patent evaluation procedure.

3. The sample selection

3.1 The whole longitudinal data set

We combine the information collected from the data sources described above, and we restrict our sample to those years with non-missing information on the variables of our main interest, thus creating an unbalanced panel data set comprising 87,698 firm-year observations referring to 13,695 target companies. When a single target company is involved in multiple equity deals, we consider the first deal within our sample period.[10] With the exception of the deals registered at the beginning and at the end of the considered period, the yearly number of equity deals is quite uniformly distributed across the sample period. It is worth pointing out that a lower number of deals is registered in 2009, i.e. in the aftermath of the financial crisis, while a higher than average number of deals is registered in the years 2014 and 2015.

[10] This choice is not relevant for the conclusions of our analysis. Only around 15 per cent of the target companies in our sample are involved in more than one deal. All the main results of our regression analyses are confirmed when excluding these companies from the data set.

Deals are classified according to the investor type, so that deals with at least one development financial institution among the investors (*DFIbacked*) are compared with those that are not backed by any DFIs.[11] Table 1 shows that the percentage of deals including at least one DFI among the investors increases from 6.5 per cent in 2007–2011 to nearly 9 per cent in 2012–2017 (for a total of 1,081 deals out of the 13,695 deals in the sample period).

[TABLE 1 AROUND HERE]

Further information emerges when we analyse the deals backed by at least one DFI (Table 2). It is interesting to observe that a DFI rarely carries out a financial transaction without any partnership. Only 282 out of the 1,081 selected *DFIbacked* deals include exclusively DFIs on the investor side (*DFIonly* deals). In 74 per cent of the *DFIbacked* deals, DFIs are in partnership with other non-DFI investors (*DFIpartner* deals).

[TABLE 2 AROUND HERE]

Looking at the full sample (Table 3), roughly 40 percent of the 87,698 firm-year observations refer to a pre-deal period (including the year of the deal). Post-deal observations where the deal includes at least one DFI among its investors constitute nearly 8 per cent of all the observations referring to the post-deal period (excluding the year of the deal), confirming the good coverage of the years under investigation for both DFIs (*Post-deal DFI-backed*) and non-DFIs (*Post-deal no-DFIs backed*).

[TABLE 3 AROUND HERE]

3.2 The sample selection with the propensity score matching

We are aware that the possibility of interpreting our results in terms of causality is threatened by a potential selection bias issue. Indeed, target companies may be selected by DFIs according

[11] Among the DFI-backed deals, we also include deals involving direct or (second-order) indirect subsidiaries that are more than 25 per cent owned by the main DFIs.

to some characteristics, possibly including their innovative capacity. If firms' characteristics affect both the probability of being involved in a deal backed by DFIs and their post-deal innovation activity, then our empirical strategy may potentially lead to biased estimates. Indeed, in the post-deal period, divergences in the firms' patenting activity across target companies backed by different types of investors may simply reflect pre-deal differences between DFIs and other investors in their ability or propensity to select innovative firms in the equity deal.

Given the non-random assignment of the treatment, we adopt a quasi-experimental design to reduce the risk of our results being affected by a potential endogeneity issue. In particular, we recur to propensity score matching (PSM) to select a subsample of firms that are not backed by any DFIs which, in the pre-deal period, are not statistically different from the DFI-backed companies with respect to some relevant characteristics. This approach ensures that differences in the pre-deal patenting activity across the two groups are not statistically significant.

Through the PSM technique, we match the DFI-backed deals with deals that are not backed by any DFIs. In particular, a logit model allows estimating the propensity score, that is the probability of being targeted by a DFI conditional on a vector of firms' characteristics observed in the year of the deal (see Table B.2 in Appendix B for results from this first-stage propensity model). Specifically, the following covariates are included: the natural logarithm of total assets of the target firm (*Size*); the ratio of tangible fixed assets to total asset (*Tangibility*); the ratio of intangible fixed assets to total assets (*Intangible Intensity*); the ratio of EBIT to total assets (*Profitability*); the natural logarithm of the patent stock (*Patent*)[12]; the natural logarithm of age in the deal year (*Age*); a dummy variable for publicly listed companies (*Listed*); and also dummy variables for the macro area and the industry of the target firm and for the year of the

[12] Following previous research (Amess et al., 2016; Bertoni and Tykvová, 2015; Guadalupe et al., 2012), inventions developed by the companies of our sample are measured by the yearly stock of patent applications, where a yearly 15 per cent depreciation rate is applied, consistently with the main literature (Griliches, 1990).

deal[13]. Then, after sorting the data set according to a randomized order, for each DFI-backed firm, we select up to three firms that are not backed by any DFIs according to the nearest propensity scores within the same macro area, industry, and deal year.

Figure 1 shows the good quality of the matching procedure adopted. Indeed, differences in the propensity score distribution between the DFI-backed firms ('treated' group) and the no-DFIs backed firms ('control' group) significantly decrease after the matching.

[FIGURE 1 AROUND HERE]

Table 4 reports descriptive statistics for the covariates used for the propensity score matching. Differences between the two groups are reported before and after the matching procedure, respectively. Descriptive statistics show statistically significant pre-matching differences. Target firms involved in DFI-backed deals show a significantly lower size, tangibility and profitability, and they are also significantly younger than target firms in the control sample (no-DFIs backed firms). However, they show a significantly higher intangible intensity and a higher patent stock. This evidence suggests that DFIs are likely to invest in firms with an already higher innovation attitude.[14]

Conversely, the results of the two-sample t-test show that, for all the considered variables, these differences do not persist after the PSM procedure. The high p-value allows the conclusion that, after matching, there are no significant differences across the groups in the pre-deal period, a result which holds for the patent variable as well.

[13] See also Table B.1 in Appendix B for variables' definitions.

[14] Notably, the finding that development financial institutions are involved in equity deals where the target company starts from higher levels of patent stock is relevant per se, since it represents 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.

We also test the overlap condition and the result shows that the probability of receiving treatment is strictly within the unit interval, thus implying there is sufficient overlap in the characteristics of treated and untreated units to find adequate matches.

This procedure allows for a first addressing of the potential endogeneity issue. Since the control group is not statistically different from the treated one in the pre-treatment period, potential differences in the mean outcome among the two groups in the post-treatment period can be attributed to the treatment.

[TABLE 4 AROUND HERE]

Interestingly, the distribution of equity deals by activity class of the target firm also reveals that DFIs tend to shift financial resources toward *High-tech Knowledge-intensive services* (in particular, *Scientific Research and Development (NACE code 72)* and *Computer programming, consultancy and related activities (NACE code 62)*) and *High-technology manufacturing* (in particular, *Manufacture of Computer, Electronic and Optical Products (NACE code 26)*), at the expense of *Less knowledge-intensive market services* (in particular, *Retail Trade (NACE codes 46–47)*).

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. The relevance of DFIs in deals concerning industries at the technological frontier justifies our interest in explaining the effect of the financial support of DFIs on the innovative activity of the target companies. Again, the different distribution by activity class becomes not significant in the matched sample.

4. Empirical strategy

We are interested in examining whether deals involving DFIs affect the innovation activity of target firms. Our approach is aimed at addressing the general question about the DFIs'

capacity to support innovation, by analysing how the firms' patenting activity has varied over time (from the years preceding the first deal to the following years) and across groups (firms financially supported or not supported by DFIs).

In this section, we present the empirical strategy adopted to address our research question, which consists of more stringent models to lower the risk of post-deal differences being potentially driven by differences across DFIs and non-DFIs in their selection strategy. First, we adopt an OLS two-way fixed effect (TWFE) estimator to compare the post-deal variation in the patenting activity between target companies backed and not backed by DFIs, while controlling for firm-specific and time-specific confounders. Second, we extend the traditional TWFE model by explicitly considering multiple timing in the treatment. In particular, we address our research question through a panel event study and a staggered diff-in-diff approach.

Moreover, each regression model is tested both on the whole before-matching sample and on the smaller matched sample selected with the propensity score matching procedure.

4.1 Two-way fixed effects

To study the impact of financial support granted by DFIs on the target companies' innovative capacity, we first adopt an OLS two-way fixed effect estimator (TWFE) with standard errors being robust to heteroscedasticity. The TWFE allows controlling for time-invariant differences across firms and year fixed effects, thus avoiding a potential bias deriving from the omission of unobservable firm-specific and year-specific confounders that cannot be included in the PSM procedure (Blundell et al., 2002). This model specification allows us to control for the unobserved heterogeneity that might affect our estimates. Moreover, according to the diff-in-diff approach, the baseline specification of our TWFE is given by:

$$y_{i,t} = \alpha + \gamma PostDeal_{i,t} + \delta PostDeal_{i,t} * DFIbacked_i + \boldsymbol{X}'_{i,t}\theta + \mu_i + \vartheta_t + \varepsilon_{it} \qquad [1]$$

where the dependent variable $y_{i,t}$ is the stock of patents of target company i in year t.[15] μ_i and ϑ_t represent respectively firm and time fixed effects. The former captures time-invariant differences across target firms, including differences in the pre-deal patenting activity. The latter captures time-dependent common shocks, including macroeconomic exogenous shocks.

$PostDeal_{i,t}$ is a dichotomous variable taking the value of 1 in the years following the deal and 0 otherwise. Its coefficient γ measures how the patent activity of companies that are not backed by any DFIs has varied in the years following the equity deal, thus pointing out whether the financial support granted through the deal is associated with an increase in the firm's innovative activity; $DFIbacked_i$ is a dichotomous variable taking the value of 1 when the target firm i has been financially supported by at least one DFI and zero otherwise. δ, the coefficient on the interaction term $PostDeal_{i,t} * DFIbacked_i$, measures the differential effect on post-deal patenting activity of the target companies that received the financial support of at least one DFI compared to those targeted exclusively by other investors. Therefore, the sign and size of δ is relevant to assess whether the presence of a DFI in the deal is associated with an incremental effect on the target company's innovative capacity.

This baseline model is expanded to further distinguish deals backed exclusively by DFIs (*DFIonly*) and deals backed by DFIs in partnership with other investors (*DFIpartner*).

We also control for potential confounding factors. The vector $\boldsymbol{X'}_{i,t}$ includes a set of covariates recognized as relevant to explain the firm innovative activity. Specifically, we include: operating revenues, used as a proxy for the size of the company; tangible fixed assets, as a measure of the firm's capital expenditures; intangible fixed assets as a proxy for internal

[15] To reduce the potential incidence of outliers, in the main regressions we use a logarithmic transformation of the dependent variable (Bertoni and Tykvová, 2015; Chemmanur et al., 2014). We do not use the logarithmic transformation when introducing negative binomial models in the robustness checks.

R&D effort, since data on R&D expenditures are mainly unavailable.[16] All these financial characteristics are log-transformed for estimation purposes. Again, we also consider whether the firm is listed on a stock exchange and include the age of the firm among the explanatory variables. Descriptive statistics for all these variables are reported in Table B.3 in Appendix B.

The choice of using the patent stock as dependent variable could raise a problem of spurious correlation. To address this issue, in a second step we also add the 1-year lagged dependent variable among the regressors. Then we recur to the difference generalized method-of-moments estimator, Diff-GMM (Arellano and Bond, 1991; Holtz-Eakin et al., 1988), in order to deal with the biased estimates that typically affect OLS fixed effects methods when applied to the dynamic model (Baltagi, 2001; Nickell,1981).

4.2 Diff-in-diff with multiple treatment

Next, we extend the traditional TWFE model to a diff-in-diffs method with multiple timing in the treatment. The traditional TWFE usually applies to a dataset composed by two groups and two time periods, and where a unique post-treatment dummy is adopted for the years occurring after the treatment. However, recent literature has highlighted that a TWFE estimator can bring to biased estimates when the treatment is not unique but varies across groups or time periods (Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfœuille, 2020; Goodman-Bacon, 2021). The intuition behind this argument is that, when multiple treatment periods are considered, the late-treated units can act as a control for the early-treated units, and vice versa.

Goodman-Bacon (2021) shows that, when the time of the treatment varies across groups, the diff-in-diff estimator is a weighted average of the multiple groups/periods diff-in-diff

[16] Intangible fixed assets 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., 2019; Marin, 2014).

estimators. In particular, the canonical TWFE estimator can be decomposed into a weighted average of all possible 2x2 TWFE models, with the weight of each 2x2 model depending on the subsample size and the timing of the treatment. This approach highlights how the canonical TWFE can provide biased estimation in case of dynamic treatment effects, notably when the size of the effect is associated with the number of the treated units or with the timing of the treatment.

4.2.1 Panel event study

To avoid biased estimations that could result by applying a standard TWFE model to a setting with heterogeneity in the time of the treatment (the year of the deal differs among firms), we first adopt a panel event study approach (Clarke and Schythe, 2020). By using as counterfactuals both untreated units and late-treated units (receiving the treatment in a following year), panel event studies are designed to estimate the impact of an event affecting units in different time periods (Athey and Imbens 2022). By denoting as $Event_i$ a variable which records the time period *t* when the event takes place for the unit *i,* the specification of the panel event study can be written as:

$$y_{it} = \alpha + \sum_{j=1}^{J} \beta_j (LAG\ j)_{it} * DFIbacked_i + \sum_{k=1}^{K} \gamma_k (LEAD\ k)_{it} * DFIbacked_i + \boldsymbol{X}'_{i,t}\theta + \mu_i + \vartheta_t + \varepsilon_{it} \qquad [2]$$

Lags and leads are defined as follows:

$$(LAG\ J)_{it} = 1[\mathrm{t} \leq Event_i - J]$$
$$(LAG\ j)_{it} = 1[\mathrm{t} = Event_i - j]\ \ for\ j \in \{1, \dots, J-1\}$$
$$(LEAD\ k)_{it} = 1[\mathrm{t} = Event_i + k]\ \ for\ k \in \{1, \dots, K-1\}$$
$$(LEAD\ K)_{it} = 1[\mathrm{t} \geq Event_i + K]$$

Lags and leads are binary variables capturing the distance between the year of the observation and the time period when the event takes place. They indicate that each unit of observation *i* is a given number of periods away from the event. The inclusion of lags and leads allows controlling for a different pre-trend across target firms and to verify the pre-trend parallel assumption. Moreover, it allows the estimation of a treatment effect which is heterogeneous in

time and to assess its temporal dynamic, for instance whether it is increasing or decreasing in time, whether it is stable or volatile, whether it is permanent or temporary.

4.2.2 Staggered diff-in-diff

A second issue that may affect the reliability of the TWFE estimator in our setting is the non-random assignment of the treatment. Indeed, investors are likely to select the target firms through an equity deal according to some observable characteristics, including their innovative capability. Though the PSM ensures that in the pre-treatment periods firms targeted by DFIs are not statistically different from those targeted by other investors, we further address this endogeneity issue broadly following Deshpande and Li (2019) and Fadlon and Nielsen (2021). They both exploit the heterogeneity in the timing of the treatment to develop a staggered diff-in-diff which is robust to the non-random and endogenous assignment of the treatment[17]. This approach allows to estimate the average treatment effect on the treated by comparing treated units receiving the treatment at different moments in time (e.g., late-treated are used as control of early-treated). As shown by the authors, the fact that both treated and control units receive the same treatment (they only vary with respect to the timing of the treatment) allows to address potential endogeneity issues stemming from the non-random assignment of treatment.

Consistently with their approach, we develop a staggered diff-in-diff design, where the treated units are categorized into groups (or cohorts) according to the year when they first receive the treatment. Specifically, we rearrange our data as follows. For each deal year t (with $t=1..n$), we select the firms targeted in that year t (treated group) and those firms that within the

[17] In particular, Fadlon and Nielsen (2021) assess the effect of several health shock on family labour supply. Since health shocks do not occur randomly, the authors build a counterfactual using households that experience the same shock a few years apart. Using a similar approach, Deshpande and Li (2019) estimate the effect of closings of Social Security Administration field offices on the number of disability recipients. Since the closing of an office is not an exogenous random treatment, offices that have been kept open do not represent a good control for those that have been closed. Therefore, the authors exploit the variation in the timing of the closure to build a control group composed as well by treated units, which nevertheless receive the treatment at different times.

[*t-3; t+3*] time window are not involved in any equity deal (control group). Therefore, each control group is composed by early treated units (treatment year prior to t-3) and late treated units (treatment year after t+3). By recursively replicating this process for all deal years, we end up with n groups that are finally stacked into a unique longitudinal dataset used to run the following regression:

$$y_{igt} = \gamma_{ig} + \sum_{g=1}^{n} \gamma_{gt} + \beta PostDeal_{gt} + \delta\left(PostDeal_{gt} * DFIbacked_{ig}\right) + X'_{igt}\theta + \varepsilon_{igt} \qquad [3]$$

where the dependent variables y_{igt} is the the patent stock of the firm *i*, belonging to group *g*, in the year *t*; γ_{ig} are firm-level fixed effects for the firm *i* within the group *g* (notice that the same firm can appear as a control or a treated unit in different groups *g*), while γ_{gt} are time fixed effects referring to the year *t* within the group *g*. $DFIbacked_{ig}$ is a dummy equal to 1 if the firm *i* is a treated unit within group *g* (target of an equity deal including a DFI among its investors), while $PostDeal_{gt}$ is a dichotomous variable that, within each group *g*, takes the value of 0 in the pre-deal period and 1 thereafter. Our coefficient of interest is δ, which captures the differential effect of the treatment on the treated firms *i* compared to the control units in the considered group *g*. Since in the aggregated database there are repeated observations for each firm, standard errors are clustered at the firm level.

Within the entire stacked panel dataset, we distinguish deals backed exclusively by DFIs (*DFIonly*) and deals backed by DFIs in partnership with other investors (*DFIpartner*).

Next, we consider the various deal categories separately and one at a time. In particular we restrict our sample respectively to: (i) equity deals carried out exclusively by non-DFIs; (ii) *DFIonly* deals; (iii) *DFIpartner* deals. This latter approach, which corresponds to the Deshpande and Li (2019) setting, allows to assess the impact of the financial support on the firms' patenting activity by exploiting exclusively the heterogeneity in the time of the treatment, that is the variation of the year when equity deals take place. Indeed, firms receiving financial support through one of the three above-mentioned deal categories (no-DFIs deals, *DFIonly*

deals, and *DFIpartner* deals) are compared to other early or late treated firms within the same deal category, that have been targeted through an equity deal in a year outside the considered [*t-3; t+3*] time window. The fact that both treated and control groups are composed exclusively by firms within the same deal category ensures our results to be robust to potential biases deriving from the non-random assignment of the treatment.

5. Results and discussion

5.1 Main findings

TWFE. Table 5 reports the results from the estimation of the two-way fixed effects model, which is initially applied to the whole unmatched sample (columns 1–2). Results show that, *ceteris paribus*, the patent stock is positively and significantly associated with the control variables (operating revenues, tangible and intangible fixed assets, as well as age and the fact of being listed on a stock market).

The positive and statistically significant coefficient of the *PostDeal* variable indicates that the patenting activity of firms targeted by non-DFIs through an equity deal increases in the post-deal period, while the positive and significant coefficient of the interaction term *PostDeal*DFIbacked* indicates that the patents' post-deal increase is even stronger for DFI-backed target companies. Results reported in column 2 show that this latter incremental effect is driven by the *DFIpartner* subgroup: firms receiving financial support by DFIs in partnership with other investors experience the highest increase in their patenting applications. In particular, our estimates suggest that this increase is about 9 percentage points higher. Conversely, the coefficient of the interaction term is not significantly different from zero when considering the *DFIonly* subgroup. This indicates that, after receiving financial support exclusively by DFIs, target firms do experience an increase in their patenting activity which is not statistically different from those firms financed exclusively by other investors.

As anticipated, the interpretability of our results in terms of the differential impact of the DFIs' financial support on the innovation performance of the targeted firms is limited by a potential selection bias issue. To address this issue, the model is re-estimated on the propensity score matched sample (PSM sample) obtained in section 3.2, with results reported in columns 3–4 of Table 5. Estimates obtained within the matched sample corroborate our previous findings. In particular, the positive coefficient of the *PostDeal*DFIbacked* interaction confirms that the post-deal level of patent application increases more when firms are targeted through equity deals involving at least one DFI. Again, this result is driven by those deals where target companies receive financial support from DFIs in partnership with other investors (*DFIpartner*).

[TABLE 5 AROUND HERE]

This result might be explained in light of the positive synergies resulting from the collaboration among different types of investors, which show different, and potentially complementing and reinforcing, competences. According to literature, DFIs can add value when they act in partnership with non-DFIs since they leverage on their capabilities and expertise in taking and managing risk. In recent years a great effort has been done in strengthening DFIs corporate governance rules, enhancing greater transparency and disclosure, ensuring a sound and efficient board, improving managerial capabilities and oversighting the management performances (Bacchiocchi et al., 2019; Bernier et al., 2020; Karolyi and Liao, 2017; OECD 2015).[18] In addition, DFIs perform a first or early mover role by supporting risky innovative projects to create a track record which indirectly crowds-in private finance to

[18] A recent survey from the OECD focuses on the changes that have taken place in the corporate governance of state-owned enterprises (SOEs) in the last five years and highlights that on the overall there is a movement towards a more effective corporate governance framework for both SOEs and DFIs (OECD, 2020). Changes in management and governance mechanisms are also confirmed by academic literature (Khandelwal et al., 2013; Koske et al., 2015; Lazzarini and Musacchio, 2018).

innovative projects. The DFIs decision to support an innovative project may be a 'signal' for private investors to crowd-in, especially in new and unfamiliar project settings, where the DFIs may have developed a reputation for expertise (Geddes et al., 2018; Mazzucato and Semieniuk, 2017; Mertens and Thiemann, 2018). Besides, DFIs' strategies usually have 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 with an explicit policy mandate to promote socio-economic goals (Hoskisson et al., 2002).[19]

Furthermore, our main findings are also broadly confirmed when we include the lagged dependent variable among the regressors and use the difference GMM estimator. Results reported in Table 6 show that the coefficient of the interaction term $PostDeal * DFIbacked$ is lower than in the two-way fixed effects model, since the inclusion of the lagged dependent variable now captures persistence in inventions developed by the target companies. However, the coefficient is still positive and significant, thus confirming our previous finding on the positive contribution of DFI-backed deals on the firms' patent applications, this incremental effect being driven by those equity deals jointly participated by DFIs together with other investors. These results hold independently on the chosen data set (before or after matching). Moreover, statistics reported in Table 6 show that the error term is not second-order serially correlated (while it is first-order serially correlated by construction), thus confirming that we do not need to include larger lags in the model specification in order to get appropriate GMM estimations.

[19] This opposes the short-termism critique that can affect private companies redirecting resources from R&D-oriented activities to more conventional short-term ones (Porter, 1992; Stein, 1988). Evidence of short-termism has been found when looking at private enterprises listed on the stock market (Ferreira et al., 2014), especially when there is participation from speculating investors (Bushee, 1998, 2001).

We can conclude that the main findings about the positive effect of DFIs on innovation are confirmed by both the TWFE specification and the GMM approach, which are designed to address potential endogeneity issues when randomization is not feasible.

[TABLE 6 AROUND HERE]

A potential criticism might concern the choice of the explanatory variables. In Table B.4 in Appendix B, we introduce a different set of control variables, in line with the financial ratios used for the propensity score matching approach of Section 3.2. Moreover, the new control variables are one-year lagged compared to the patents' year of observation. The results are still consistent with previous findings.

Panel event study. Next, as explained in Section 4.2, we exploit the panel structure of the data and replace the $PostDeal_{i,t} * DFIbacked_i$ interaction with distinct interaction terms for each period relative to the deal year. Results of the event study specification are reported graphically in Figure 2.

The coefficients referring to the pre-deal years are not significantly different form zero, thus supporting the assumption of a parallel pre-treatment trend that needs to be satisfied for the difference-in-differences approach to provide unbiased estimates. By contrast, positive coefficients referring to the post-deal period reveal that the DFI participation (i.e. the treatment) positively affect the patenting activity of the target firm. In particular, in line with previous regressions, this positive effect is detected only if the DFI participates in partnership with other investors (graphs on the right). Since the TWFE model does not control for the lagged dependent variable, the post-deal coefficients show that DFI-backed firms tend to be on a permanently higher level of patent stock after one year from the deal (top-right graph). By contrast, the GMM approach includes the lagged dependent variables and takes into account persistence in the patent stock, thus revealing that it takes two years for the DFI participation

to reach its maximum effect on patent activity, and then this effect fades away (bottom-right graphs).

[FIGURE 2 AROUND HERE]

Interestingly, following the reasoning of Hall et al. (1986) and Lerner et al. (2011), we may argue that this lag in the change in patenting activity makes it unlikely to influence the DFIs' decision to invest and, consequently, it reduces the possibility that our main findings are due to reverse causality.

Staggered diff-in-diff. Finally, results of the *staggered diff-in-diff* are reported in Table 7. First, the analysis is conducted on the entire stacked panel dataset, which is constructed by considering all equity deals. Results reported in column 1 of Table 7 entirely confirm our previous findings. The *PostDeal* variable has a positive and significant coefficient, which captures the incremental impact of equity deals backed by non-DFIs on the target firms patent activity compared to a control group composed by firms that in the [*t-3; t+3*] time window do not receive any treatment. The positive and significant coefficient of the *PostDeal*DFIpartner* interaction term indicates that this positive effect on the firms' patenting activity is higher when deals are backed by DFIs in partnership with other investors. Finally, the positive but not significant coefficient of the *PostDeal * DFIonly* interaction term confirms that deals backed exclusively by DFIs have a positive effect on the target firms' innovation capability that is not superior nor inferior compared to the deals backed exclusively by non-DFIs.

Next, we consider the various deal categories separately and one at a time (see section 4.2.2). Column 2 reports the result of the staggered diff-in-diff estimated on the restricted sample where only equity deals performed exclusively by non-DFIs are considered. Since all the equity deals including DFIs among the investors (either exclusively DFIs or in partnership with non-DFIs) are now excluded from the dataset, the *PostDeal* variable captures the effect of equity

deals performed by non-DFI investors with respect to other non-DFIs backed firms that, within the considered time window, are not involved in any deal. Its coefficient continues to be positive and significant, with a magnitude highly comparable to the one estimated on the entire sample, confirming the positive role that investors different from the DFIs play in supporting firms' innovation capability.

We then restrict the sample to the equity deals performed exclusively by DFIs.[20] As reported in the column 3 of Table 7, the *PostDeal* variable has a positive coefficient, though it is significant only at a 10 percent level. As reported in the descriptive statistics, it is quite rare that a deal is performed exclusively by DFIs, but the results of the staggered diff-in-diff confirm the positive role played by DFIs in supporting innovation even when they act alone.

We finally restrict the analysis to the case of equity deals in partnership (column 4 of Table 7). Consistently with previous results, we estimate for the *PostDeal* variable a positive and significant coefficient, whose size is higher than in the two previous cases. This estimation confirms that the positive effect of equity deals on the target firms' patenting activity is amplified when DFIs act in partnership with other investors.

[TABLE 7 AROUND HERE]

5.2 The role of institutional quality and social spillovers

We finally investigate the possibility that our results depend on (i) the institutional quality of the countries where the DFIs are established and (ii) the social and environmental spillovers that characterize innovation in the industries where the target firms operate.

[20] In this case, the treated group, composed only by firms targeted exclusively by DFIs (*DFIonly*) in the year t, is compared to a control group composed by similar firms, which are targeted exclusively by DFIs, but in a year outside the considered [t-3; t+3] time window.

First of all, building on the existing literature on public ownership (Castelnovo et al., 2019; Clò at al., 2020), we argue that institutional quality is a relevant factor affecting the performances and effectiveness of development financial institutions. Indeed, the institutional quality of a country is likely to affect the DFIs' public management appointment procedures, their internal governance and monitoring mechanisms, and the objectives that DFIs are instructed to achieve. DFIs that are located in countries with high institutional quality are more likely to rely on internal stability, transparent monitoring and selection procedures and clear commitment towards long-term socially valuable goals. Conversely, the phenomena of political capture, orientation towards immediate personal objectives, and misallocation of resources are more likely to take place in countries characterized by low quality institutions. Therefore, we expect institutional quality to have relevant effects on both the DFIs' orientation to support innovation in the target firms and on the management internal capability to achieve these goals.

Table 8 (panel A) explores the relevance of institutional quality. Following a consolidated literature, to measure the country institutional quality we rely on the World Bank's Worldwide Governance Indicators (WGI) database (Kaufmann and Kraay, 2008; Kaufmann et al., 2011). In light of our specific interest in the quality of the government controlling the DFIs, we focus our attention on the Control of Corruption (CC) indicator, which captures "the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as capture of the state by elites and private interests" (Kaufmann et al., 2011, p. 223). Accordingly, after estimating the average value of the CC indicator, we split our sample in two sub-samples: (i) equity deals performed by investors located in higher-institutional quality countries (with a CC score above the average value); (ii) equity deals performed by investors

located in lower-institutional quality countries (below the average value). The model specification and control variables mirror those used in Table 5.[21]

In line with the above considerations, Table 8 (panel A) shows that the incremental positive effect on innovation of DFI participation is confirmed (and even stronger) in higher-institutional quality countries, while DFIs located in lower-institutional quality countries provide a very weaker incremental support to innovation (significant only at 10 percent level) when they co-finance the equity deals in partnership with other investors.

Next, we argue that DFIs are more oriented than private investors to support innovation in those sectors where innovation generates positive levels of social spillover, i.e. positive effects on economic development and the society as a whole. This view is in line with the strand of literature suggesting that private agents are unable to fully internalize the benefits of investments in goods and industries that produce positive social spillovers and, consequently, they may underinvest with respect to the social optimum (Arrow, 1962; Hall and Lerner, 2010; Nelson, 1959). Therefore, we may expect that, *ceteris paribus*, the participation of DFIs is not limited to the provision of additional equity, but is specifically aimed at shifting a higher percentage of investments from projects with a short-run commercial value to projects with long-run returns and social spillovers. Under this view, we therefore expect that the positive effect on innovation of DFI involvement is higher for target firms in the high-tech and 'green' industries, i.e. in industries with high social spillover (Fotak and Lee, 2020; Hasan ad Tucci, 2010).

[21] For the sake of brevity, columns for the PSM sample are not reported, but the results are consistent (and available upon request).

Table 8 (panel B) shows our findings after splitting our sample in the two sub-samples: (i) equity deals concerning target firms in the High-Tech & Green industries[22]; (ii) equity deals concerning target firms in all the remaining industries. The estimated coefficients confirm that the incremental positive effect on innovation of DFI participation is higher when the target firm is in industries with high social spillovers.

[TABLE 8 AROUND HERE]

This evidence supports our underlying hypothesis on the relevant role played by the DFIs in financing innovation through their participation in equity deals. Indeed, if the positive effect of DFIs' participation was only due to the additional capital they provide, there would be no reason to find stronger effects when they are headquartered in countries with high-quality institutions and target firms operate in industries with positive social spillovers.

6. 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 dependent variables are considered and with a different sample being analysed.

Negative binomial model. First of all, we tested the robustness of our main findings by adopting a negative binomial specification model with standard errors being robust to heteroscedasticity. This model generalizes the Poisson regression model by introducing latent heterogeneity in its conditional mean (Blundell et al., 1995). This choice is driven by the overdispersion of our data compared to the Poisson distribution, which assumes the sample

[22] These include: high-technology manufacturing; medium-high technology manufacturing; high-tech knowledge intensive services; electricity, gas, steam and air conditioning supply; water supply, sewerage, waste management and remediation activities (see also Table 4 for a description of the source of this classification).

variance of the patent variables being equal to the sample mean. The negative binomial is thus robust to a number of misspecifications such as over-dispersion, the presence of an excessive number of zeros, as well as cross-sectional dependence.[23] Moreover, we maintain an identification strategy in line with a difference-in-differences approach to mitigate the potential selection bias. Consequently, the baseline specification of the negative binomial regression model is given by:

$$E[y_{i,t}] = exp(\alpha + \beta DFIbacked_i + \gamma PostDeal_{i,t} + \delta PostDeal_{i,t} * DFIbacked_i + \boldsymbol{X}'_{i,t}\theta + \vartheta_t + \varepsilon_{it}) \qquad [4]$$

where δ still captures the difference-in-differences effect on patenting activity of being supported by at least one DFI. This model specification still includes year fixed effects but does not include firm fixed effects anymore. For this reason, we also include among the regressors dummy variables for geographical and sectoral fixed effects to control for time-invariant differences of the target companies.[24] Moreover, we add the non-interacted $DFIbacked_i$ variable, which is not absorbed anymore by firm fixed effects. The coefficient β on this variable measures the difference in pre-deal patent activity between companies backed by at least one DFI and companies that are not supported by any DFIs.

Table 9 reports the results from this alternative specification. The results obtained within the whole sample (column 1) confirm the positive and highly significant coefficient of the interaction term $PostDeal * DFIbacked$. On average, after being targeted in equity deals, DFI-backed target companies experience higher increase in patenting activity than non-DFI-backed

[23] Various papers use the negative binomial model for an unbalanced panel to estimate the determinants of innovative activities (Allison and Waterman, 2002; Castelnovo et al., 2018; Furman and Stern, 2011). 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.

[24] 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.

target companies. Estimates also confirm that this result is driven by deals where DFIs join other investors in a partnership while no differential effect is detected when DFIs are the only funding institutions (column 2). These findings are widely confirmed within the reduced matched sample (columns 3 and 4).

[TABLE 9 AROUND HERE]

Interestingly, the coefficient on the *DFIbacked* dummy variable is positive and significant in the whole sample (columns 1-2) but not in the PSM sample (columns 3-4), confirming the goodness of the matching procedure.

We also use a zero-inflated negative binomial (ZIB) estimator to explicitly account for the high prevalence of zeros in the dependent variable.[25] Results reported in Table B.5 in Appendix B confirm our previous findings, thus being robust to zero outcomes as well as over-dispersion of the count data (Cameron and Trivedi, 2005; Greene, 1997; Hausman et al., 1984; Mullahey, 1986).[26]

Time window [t-3;t+5]. We are aware that our data sample may be affected by a truncation problem due to the lower probability of detecting post-deal patenting activity for target firms of deals occurring at the end of the period and, similarly, the lower availability of pre-deal financial data for target firms of deals occurring at the beginning of the period. In order to mitigate the effect of data truncation we re-estimate the impact of DFIs on patent activity

[25] The ZIB is based on a zero-inflated probability distribution, that allows for frequent zero-valued observations. It is structured in two parts: a logit model, which predicts the probability of not patenting, is fitted into a negative binomial model.

[26] It is possible to show that these findings are widely confirmed when a hurdle negative binomial regression model is used as an 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. Results of the Hurdle negative binomial are not reported and are available upon request.

restricting our sample to a different time window around the event (i.e. the equity deal). In particular, for each target company we only consider observations in a time window from three years before to five years after the corresponding deal took place. Considering the results within the PSM sample, Table 10 shows that the positive coefficient on the interaction term *PostDeal * DFIpartner* estimated within the *[t-3;t+5]* time window is very similar to the impact estimated without time restrictions (Tables 5 and 6).

[TABLE 10 AROUND HERE]

Granted and citation-weighted patents. An increase in the 'quantity' of patents does not necessarily imply an improvement in the 'quality' of the patenting activity. Thus, in order to capture quality, we also introduce an alternative definition for our dependent variable. First, we only consider granted patents, while excluding from our patent counting those patents that have been filed but not (yet) granted. Second, we weight each patent by the number of citations it received after the grant (Hall et al., 2005; Harhoff et al., 1999). Table 11 shows the results obtained after introducing granted and citation-weighted patents as the new measure of our dependent variables. Comparing these results with those of Tables 5 and 6, we find an even higher differential impact of DFIs when they invest in partnership with other investors (*DFIpartner*), while the differential impact is negative and statistically significant when they invest alone (*DFIonly*) according to the two-way fixed effects estimator.

[TABLE 11 AROUND HERE]

For the sake of space, only estimates for the PSM sample are reported in Table 11, but the same findings are obtained within the whole sample, and even more encouraging in terms of the role of DFIs (see Table B.6 in Appendix B).

Location effect. We finally perform an additional robustness check to consider explicitly the presence of possible 'location effects', i.e. the possibility of our results to be driven by DFIs

located in single countries. We run again the two-way fixed effects models by excluding one by one each single country (depending on the headquarter of the DFI) from our dataset. In Table 12 we report the results obtained when equity deals backed by French or German DFIs are excluded from the analysis, since France and Germany are the two countries with higher number of DFI-backed deals and DFIs, respectively. Our results are validated and are also confirmed for the other unreported estimates obtained by excluding equity deals backed by DFIs in the other single countries (results are available upon request).

[TABLE 12 AROUND HERE]

7. Conclusions

This paper is about European DFIs and their role in providing financial support to innovation. DFIs, defined by the European Commission as legal entities carrying out financial activities on a professional basis which are given a mandate by a member state to carry out development activities, have evolved dynamically over the last decades and nowadays they are sharing the management of EU financial instruments and are acting as co-financers or co-investors to provide long-term finance to enterprises and to boost innovation. Indeed, in the aftermath of the 2008 financial global crisis, the 2011 sovereign debt crisis and the more recent Covid-19 pandemic, their activity has become crucial in restructuring the economy and channeling leveraged funds into the market, especially for addressing the financing needs of innovative sectors, like innovative start-up and SMEs, that traditionally find it difficult to access finance because of lack of guarantees and collaterals, lack of track records, difficulties in evaluating the business and the innovation process.

Although the innovative-oriented mission of DFIs is widely stated in their statutes and also highlighted in some recent literature (see Introduction), to the best of our knowledge it has never been documented through empirical analysis. In our paper we aim to fill this gap by

empirically evaluating whether EU DFIs effectively support innovation. To this end, we analyse equity deals to investigate how the innovative activity of the target companies is affected by the participation of development financial institutions as investors.

The empirical analysis leverages on a unique, manually collected dataset that includes all the DFIs headquartered in Europe (reported in Appendix A). The empirical strategy is based on a quasi-experimental design which allows to address potential endogeneity issues. We first combine a Propensity Score Matching with a TWFE estimator. Next, we extend it by explicitly considering multiple timing in the treatment. Through a panel event study approach, we first estimate a dynamic treatment effect which highlights its temporal dimension and allows to test for the parallel trend assumption. Finally, we develop a staggered diff-in-diff design that, by fully exploiting the heterogeneity in the time of the treatment, ensures our results to be robust to potential biases deriving from the non-random assignment of the treatment.

Our results are twofold. First, financial support through equity deals is associated to an increase in the patent application of the target firms, and this increase is higher when DFIs act in partnerships with other investors. Second, target firms receiving financial support exclusively by DFIs experience an increase in their patenting activity which is not statistically different from those firms financed exclusively by other investors. These findings, which are robust to alternative econometrical specifications, point to the positive role played by DFIs in supporting innovation, coherently with their internal mandates, and highlight the positive synergies that arise when different types of investors contribute with complementing and reinforcing competences.

Relevant literature brings some insights to understand why DFIs can add value when they act in partnership with non-DFIs. Indeed, DFIs leverage on their capabilities and expertise in taking and managing risk, and perform a first or early mover role by supporting risky innovative projects to create a track record which indirectly crowds-in private finance to innovative

projects. As highlighted in Geddes et al. (2018) and Mazzucato and Semieniuk (2017), the DFIs decision to support an innovative project may be a 'signal' for private investors to crowd-in, especially in new and unfamiliar project settings, where the DFIs may have developed a reputation for expertise. Besides, 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 with an explicit policy mandate to promote socio-economic goals (Hoskisson et al., 2002). Interestingly, this result is consistent with various studies revealing the added value of public–private partnerships for the delivery of long-term goals in other research areas such as blended finance (European Investment Bank, 2014, 2018; OECD, 2017, 2018a, 2018b, 2018c) and venture capital (Bertoni and Tykvová, 2015; Brander et al., 2014; Cumming et al., 2017; Grilli and Murtinu, 2014).

Our hypothesis on the positive role played by DFIs is also strengthened by the evidence that the incremental positive effect on innovation is even higher (i) when DFIs are located in high-institutional quality countries, where they are more likely to rely on internal stability, transparent monitoring and clear commitments towards long-term socially valuable goals and (ii) for target firms in the high-tech and 'green' industries that generate positive spillovers on economic development and the society as a whole. If the positive effect of DFIs' participation was only due to the additional capital they provide with respect to other investors, there would be no reason to find these heterogenous effects.

The role of DFIs in providing financial support through equity deals represents novel evidence on the innovative-oriented mission driving their financial activity. This evidence emphasizes the role DFIs are called upon to play by the European Commission, which recently specified that "*Member States that do not yet have a national promotional bank may consider setting one up*" (European Commission, 2015, p.2). At the same time, the fact that results are

stronger when DFIs intervene together with other types of investors stresses the importance that they do operate in synergy with the private sector, complementing and reinforcing their mutual strengths.

Interesting further development of future research may focus on differences in the characteristics of DFIs in terms of governance structure, internal control procedures, professional management and degree of independence, in order to disentangle the effects of changes in corporate governance rules and regulatory frameworks that in the last decade have shaped the contemporary features and roles of DFIs (OECD 2005, 2011, 2012). Finally, based on microdata from single DFIs, which are generally not publicly available, the potential impact of DFIs on innovation may be investigated by means of non-equity instruments, such as loans and guarantees, and subsidies.

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Appendix

A. DFIs in Europe

[TABLE A.1 AROUND HERE]

The population of DFIs in Europe includes:

i. very large multilateral development banks operating at a supranational level and set up by a group of sovereign states that are their ultimate shareholders (e.g. the European Investment Bank EIB, the European Bank for Reconstruction and Development EBRD, and the Nordic Investment Bank NIB);
ii. national development banks (e.g. the German Kreditanstalt fur Wiederaufbau KfW, the Italian Cassa Depositi e Prestiti CDP, and the French Caisse des Dépôts et Consignations CDC);
iii. smaller regional promotional banks (e.g. Hamburgische Investitions- und Foerderbank, Institut Catala de Finances, and Finlombarda Spa).

In addition, some development financial institutions are very old, such as the CDP founded in Italy in 1850 or the KfW founded in Germany in 1948, while others have been recently founded, such as the Instituicao Financeira do Desenvolvimento (IFD), launched in Portugal in 2014, or the Banque Publique d'Investissement (BPI) founded in France in 2012.

In terms of distribution by country, the highest number of development financial institutions are found in Germany (18), followed by Italy (10), France (9) and Belgium (9). The number of development financial institutions that operate at a supranational level is equal to 9. In 2018, development financial institutions located in Germany accounted for 33.2% of the European development banks' total assets, followed by supranational development institutions (26.4%), institutions located in Italy (15.3%), and in France (10.7%). This incidence is strongly affected by the different average size of development banks within each country. For example, in Italy

there is a large national promotional bank, Cassa Depositi e Prestiti (whose total assets amounted to approximately 425,083 million euros in 2018), and some much smaller regional entities (the largest of which is the Banca del Mezzogiorno – Mediocredito Centrale, with about 2,350 million euros of total assets). A similar situation can be observed in France, where Caisse des Dépôts et Consignations-Groupe Caisse des Dépôts (about 163,002 million euros of total assets) coexists with other national institutions operating on a much lower scale. The case is different in Germany, where KfW (about 485,790 million euros) is accompanied by the presence of some other institutions of considerable size, such as the NRW.Bank (with about 149,083 million euros of total assets).

The range of alternative financial products they offer has increased over the years and nowadays is generally constituted not only by loans (mainly long-term), trade finance (import/export) and guarantees, but also by equity stakes. Indeed, in recent years, development banks have set up equity instruments, such as venture capital and seed funds, to finance start-up and young firms, as well as strategic equity investments in companies of national interest. For example, the Instituto de Credito Oficial (Spain) has a venture capital firm named Axis, which provides enterprises with capital and quasi-capital instruments to finance their growth and participate as a shareholder in the Spanish Development Corporation COFIDES. Similarly, Cassa Depositi e Prestiti (Italy) holds controlling stakes in utilities of national relevance, such as Italgas, Terna, Eni, Posteitaliane, and promotes venture capital with the platforms ITATech and Social Impact Italia. Development banks also offer non-financial services, such as technical and administrative assistance, advisory services and training programmes.

With regards to liabilities, development banks rely on a mix of funding sources other than budget allocations from governments, such as loans from other financial development institutions, debt instruments issued on capital markets, and funding from European programmes, like the above-mentioned European Fund for Strategic Investments and the

European Advisory Hub. They are usually not allowed to raise funds directly via retail deposits, although there are some exceptions, such as the Bulgarian Development Bank (BDB), and, to a different extent, the Italian Cassa Depositi e Prestiti, which indirectly relies on deposit funding raised via postal saving products.

With regard to their legal features, DFIs are generally established on the basis of a specific legislative intervention, are subject to various mechanisms of government control, and enjoy a selective application of banking regulations and prudential supervision. In addition, they usually enjoy a special state guarantee but, at the same time, their activities do not affect the public budget since they are excluded from the list of subjects that contribute to the definition of the consolidated income statement for the purposes of the European accounting system. For example, KfW is a public law institution established with the 5 November 1948 Law Concerning Kreditanstalf fur Wiederaufbau and owned by the Federal Republic of Germany Bund (80 per cent) and the States of Germany Lander (20 per cent). The legal supervision is carried out by the Ministry of Finance in consultation with the Federal Ministry for Economics and Technology, who also determine which banks' supervisory laws and regulations apply to KfW, in whole or in part. Similarly, the CDP is a public financial institution owned by the Italian Ministry of Economy and Finance, 83% of the share capital, and several banking foundations for the remaining. In December 2003 it was transformed into a joint-stock company, and the State's assets and shareholdings transferred to CDP S.p.A. were assigned to a "separate account system". Similarly to KfW, only part of the banking regulation is applied to CDP, that is the provisions of Part V of the Consolidated Banking Act (Legislative Decree No. 385, 1 September 1993) applicable to intermediaries registered in the special list of Article 107 of the said Decree. Finally, the CDC is a public group created directly under the control of the Parliament, governed by the French Monetary and Financial Code, amended by the 2008-776 law on modernization of the economy, which also regulate which banking regulation and

supervision is applied to the institution. Two laws grant its highly protective status: the Immunity to liquidation and bankruptcy (French law of 25 January 1985 - art L 631-2 and L 640-2 of the French commercial code), and the Solvency protection (French Law 80-539 of 16 July 1980).

B. Additional Tables

[TABLE B.1 AROUND HERE]

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Table 1. Deals yearly distribution. Type of investors.

	Number of deals without DFIs (no-DFIs deals)	Number of deals with at least one DFI (*DFIbacked* deals)	Total
2007	246	15	261
2008	1,466	73	1,539
2009	922	81	1,003
2010	1,280	90	1,370
2011	1,291	103	1,394
2012	1,269	133	1,402
2013	1,295	135	1,430
2014	1,564	142	1,706
2015	1,586	138	1,724
2016	1,258	123	1,381
2017	437	48	485
Total	12,614	1,081	13,695

Table 2. Number of deals. Type of investors.

	Deal	
	Number	Percentage (%)
No-DFIs deals	12,614	92.1
DFIbacked deals, of which:	1,081	7.9
DFIonly deals	*282*	*2.1*
DFIpartner deals	*799*	*5.8*

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

	Freq.	Percentage (%)
Pre-deal	36,503	41.6
Post-deal no-DFIs	47,262	53.9
Post-deal *DFIbacked*, of which:	3,933	4.5
Post-deal - *DFIonly*	*1,170*	*1.3*
Post-deal - *DFIpartner*	*2,763*	*3.2*
Total	87,698	100.0

Table 4. Target characteristics in the deal year: t-test before and after PSM

	Whole Sample				PSM Sample			
Target Firm Characteristics	No DFIs	DFI backed	t-stat	p-value	No DFIs	DFI backed	t-stat	p-value
Size (= Total Assets, ln) (lag)	8.90	8.43	-5.62	0.00	8.56	8.45	-1.11	0.27
Tangibility (lag)	0.14	0.12	-2.24	0.03	0.12	0.12	0.13	0.89
Intangible Intensity (lag)	0.13	0.18	6.15	0.00	0.17	0.18	1.44	0.15
Profitability (lag)	0.00	-0.09	-4.67	0.00	-0.08	-0.09	-0.22	0.83
Age	2.25	2.04	-5.55	0.00	2.07	2.07	-0.16	0.87
Listed	0.07	0.06	-1.06	0.29	0.06	0.06	-0.41	0.68
Patent	0.30	0.49	6.02	0.00	0.44	0.5	1.23	0.22
Activity Classes								
Agriculture, Forestry and Fishing	0.00	0.01	1.29	0.20	0.00	0.00	0.02	0.99
Mining and Quarrying	0.00	0.00	-0.20	0.84	0.00	0.00	-0.68	0.50
Construction	0.03	0.02	-0.86	0.39	0.02	0.02	0.01	0.99
Electricity, Gas, Steam and Air Cond.	0.02	0.01	-1.02	0.31	0.01	0.01	-0.09	0.93
High-tech knowledge intensive services	0.22	0.29	4.38	0.00	0.29	0.29	-0.02	0.98
High-technology Manuf.	0.04	0.08	5.25	0.00	0.07	0.08	0.94	0.35
Knowledge intensive financial services	0.07	0.08	0.96	0.34	0.09	0.08	-0.24	0.81
Knowledge intensive market services	0.12	0.13	0.89	0.37	0.13	0.14	0.34	0.73
Less knowledge intensive market services	0.23	0.14	-5.48	0.00	0.15	0.14	-0.65	0.51
Low technology Manuf.	0.07	0.06	-1.21	0.23	0.06	0.06	0.06	0.95
Medium-high technology Manuf.	0.06	0.07	0.49	0.62	0.07	0.06	-0.06	0.95
Medium-low technology Manuf.	0.05	0.05	-0.42	0.67	0.05	0.05	0.29	0.78
Other knowledge intensive services	0.07	0.05	-1.72	0.09	0.05	0.05	0.04	0.97
Other less knowledge intensive services	0.01	0.00	-1.38	0.17	0.00	0.00	-0.50	0.62
Water Supply; Sewerage, Waste Manag.	0.01	0.00	-1.47	0.14	0.00	0.00	-0.50	0.62

Following Eurostat classification ('Statistics on high-tech industry and knowledge-intensive services'), 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. OLS TWFE

Dependent variable: Patent (applications)

	Whole Sample		PSM Sample	
	(1)	(2)	(3)	(4)
PostDeal	0.018***	0.018***	0.022**	0.022**
	[0.003]	[0.003]	[0.009]	[0.009]
PostDeal * DFIbacked	0.062***		0.028	
	[0.016]		[0.019]	
PostDeal * DFIonly		-0.003		-0.040
		[0.022]		[0.025]
PostDeal * DFIpartner		0.092***		0.059**
		[0.021]		[0.023]
Age	0.006***	0.006***	0.013***	0.013***
	[0.001]	[0.001]	[0.002]	[0.002]
Listed	0.030*	0.030*	0.047*	0.049**
	[0.016]	[0.016]	[0.025]	[0.025]
Tangible Assets, ln	0.005***	0.005***	0.010***	0.010***
	[0.001]	[0.001]	[0.003]	[0.003]
Intangible Assets, ln	0.003***	0.003***	0.004	0.003
	[0.001]	[0.001]	[0.002]	[0.002]
Operating Revenues, ln	0.004***	0.004***	0.001	0.000
	[0.001]	[0.001]	[0.003]	[0.003]
Obs.	87,698	87,698	18,436	18,436
No. of individuals	13,695	13,695	2,435	2,435

*** p<0.01, ** p<0.05, * p<0.1; robust standard errors are reported in brackets

Table 6. DIFF-GMM

Dependent variable: Patent (applications)

	Whole Sample		PSM Sample	
	(1)	(2)	(3)	(4)
PostDeal	0.007***	0.007***	0.005	0.005
	[0.002]	[0.002]	[0.005]	[0.005]
PostDeal * DFIbacked	0.020***		0.017***	
	[0.004]		[0.006]	
PostDeal * DFIonly		0.010		0.008
		[0.007]		[0.010]
PostDeal * DFIpartner		0.024***		0.021***
		[0.005]		[0.007]
Age	-0.001***	-0.001***	-0.002*	-0.002*
	[0.000]	[0.000]	[0.001]	[0.001]
Listed	0.007	0.007	0.010	0.010
	[0.009]	[0.009]	[0.028]	[0.028]
Tangible Assets, ln	0.002***	0.002***	0.003**	0.003**
	[0.000]	[0.000]	[0.001]	[0.001]
Intangible Assets, ln	0.002***	0.002***	0.002**	0.002**
	[0.000]	[0.000]	[0.001]	[0.001]
Operating Revenues, ln	0.001	0.001	0.001	0.001
	[0.001]	[0.001]	[0.001]	[0.001]
Patent (lag)	0.637***	0.637***	0.665***	0.664***
	[0.015]	[0.015]	[0.033]	[0.034]
Obs.	59,471	59,471	13,272	13,272
No. of individuals	10,986	10,986	2,241	2,241
No. of instruments	71	72	71.000	72.000
AR1 (p-value)	0.000	0.000	0.000	0.000
AR2 (p-value)	0.296	0.298	0.291	0.294

*** p<0.01, ** p<0.05, * p<0.1; robust standard errors are reported in brackets

Table 7. Staggered diff-in-diff

	Whole sample	Exclusively no-DFIs deals°	Exclusively *DFIonly* deals°°	Exclusively *DFIpartner* deals°°°
	(1)	(2)	(3)	(4)
PostDeal	0.030***	0.031***	0.057*	0.105**
	(0.007)	(0.007)	(0.030)	(0.042)
PostDeal * DFIonly	0.007			
	(0.027)			
PostDeal * DFIpartner	0.106***			
	(0.038)			
Constant	0.332***	0.309***	0.538***	0.658***
	(0.013)	(0.014)	(0.076)	(0.083)
Observations	39,942	37,170	980	1,792
Number of individuals	5,706	5,310	140	256

*** p<0.01, ** p<0.05, * p<0.1; robust standard errors are reported in brackets

Note: usual controls are applied in the regression but omitted from the table; ° Exclusion of firms targeted in *DFIonly* deals and *DFIpartner* deals; °° Exclusion of firms targeted in no-DFIs deals and *DFIpartner* deals; °°° Exclusion of firms targeted in in no-DFIs deals and *DFIonly* deals.

Table 8. OLS TWFE – Heterogeneous effects by country and industry

Panel A: Institutional Quality

Dependent variable: Patent (applications)				
	Higher-institutional quality countries		Lower-institutional quality countries	
	(1)	(2)	(3)	(4)
PostDeal	0.059***	0.059***	0.063***	0.063***
	[0.005]	[0.005]	[0.005[	[0.005]
PostDeal * DFIbacked	0.128***		0.023	
	[0.029]		[0.018]	
PostDeal * DFIonly		0.018		-0.009
		[0.04]		[0.026]
PostDeal * DFIpartner		0.167***		0.041*
		[0.036]		[0.024]
Obs.	45,080	45,080	42,618	42,618

Panel B: High-Tech & Green industries

Dependent variable: Patent (applications)				
	High-Tech & Green industries		Other industries	
	(1)	(2)	(3)	(4)
PostDeal	0.029***	0.029***	0.013***	0.013***
	[0.007]	[0.007]	[0.003]	[0.003]
PostDeal * DFIbacked	0.073**		0.045**	
	[0.029]		[0.018]	
PostDeal * DFIonly		-0.029		0.013
		[0.046]		[0.023]
PostDeal * DFIpartner		0.107***		0.063***
		[0.034]		[0.024]
Obs.	31,357	31,357	56,341	56,341

*** p<0.01, ** p<0.05, * p<0.1; robust standard errors are reported in brackets

Table 9. Negative binomial model

Dependent variable: Patent (applications)				
	Whole Sample		PSM Sample	
	(1)	(2)	(3)	(4)
PostDeal	0.705***	0.706***	0.620***	0.621***
	[0.050]	[0.050]	[0.071]	[0.072]
DFIbacked	0.392***		0.003	
	[0.096]		[0.084]	
PostDeal * DFIbacked	0.451***		0.345***	
	[0.127]		[0.119]	
DFIonly		0.300		-0.380**
		[0.255]		[0.188]
PostDeal * DFIonly		0.168		0.081
		[0.308]		[0.242]
DFIpartner		0.418***		0.115
		[0.084]		[0.086]
PostDeal * DFIpartner		0.544***		0.423***
		[0.124]		[0.125]
Age	0.007***	0.006***	0.005**	0.004*
	[0.001]	[0.001]	[0.002]	[0.002]
Listed	1.476***	1.517***	2.043***	2.240***
	[0.074]	[0.073]	[0.123]	[0.130]
Tangible Assets, ln	0.135***	0.136***	0.167***	0.168***
	[0.013]	[0.013]	[0.015]	[0.016]
Intangible Assets, ln	0.117***	0.118***	0.099***	0.102***
	[0.007]	[0.007]	[0.010]	[0.010]
Operating Revenues, ln	-0.063***	-0.062***	-0.039**	-0.032**
	[0.012]	[0.012]	[0.015]	[0.015]
Year, Area, Sector Fixed effects	YES	YES	YES	YES
Obs.	87,698	87,698	18,436	18,436

*** p<0.01, ** p<0.05, * p<0.1; robust standard errors are reported in brackets

Table 10. Time window [t-3; t+5] (PSM sample)

Dependent variable: Patent (applications)				
	OLS FE		DIFF-GMM	
	(1)	(2)	(3)	(4)
PostDeal	0.001	0.001	0.004	0.004
	[0.007]	[0.007]	[0.005]	[0.005]
PostDeal * DFIbacked	p0.024		0.015**	
	[0.016]		[0.007]	
PostDeal * DFIonly		-0.038*		0.007
		[0.021]		[0.010]
PostDeal * DFIpartner		0.052**		0.019**
		[0.020]		[0.008]
Age	0.020***	0.020***	-0.001	-0.001
	[0.002]	[0.002]	[0.001]	[0.001]
Listed	0.069***	0.071***	0.009	0.010
	[0.027]	[0.027]	[0.029]	[0.029]
Tangible Assets, ln	0.011***	0.011***	0.003**	0.004**
	[0.003]	[0.003]	[0.001]	[0.001]
Intangible Assets, ln	0.004*	0.004*	0.002**	0.002**
	[0.002]	[0.002]	[0.001]	[0.001]
Operating Revenues, ln	-0.001	-0.001	0.001	0.001
	[0.003]	[0.003]	[0.002]	[0.002]
Patent (lag)			0.629***	0.627***
			[0.037]	[0.038]
Firm and Year F.E.	YES	YES	YES	YES
Obs.	14,596	14,596	11,006	11,006
No. of individuals	2,435	2,435	2,236	2,236
No. of instruments			71	72
AR1 (p-value)			0.000	0.000
AR2 (p-value)			0.330	0.333

*** p<0.01, ** p<0.05, * p<0.1; robust standard errors are reported in brackets

Table 11. Granted & Citation-weighted Patents (PSM sample)

Dependent variable: Patent (granted & citation-weighted)				
	OLS FE		DIFF-GMM	
	(1)	(2)	(3)	(4)
PostDeal	0.026*	0.026*	0.012	0.012
	[0.014]	[0.014]	[0.007]	[0.007]
PostDeal * DFIbacked	0.022		0.010	
	[0.028]		[0.010]	
PostDeal * DFIonly		-0.079**		-0.024
		[0.039]		[0.016]
PostDeal * DFIpartner		0.068**		0.025**
		[0.034]		[0.012]
Age	0.021***	0.021***	-0.001	-0.001
	[0.003]	[0.003]	[0.002]	[0.002]
Listed	-0.013	-0.010	-0.021	-0.020
	[0.070]	[0.070]	[0.046]	[0.046]
Tangible Assets, ln	0.009*	0.009**	0.003	0.003
	[0.005]	[0.005]	[0.002]	[0.002]
Intangible Assets, ln	0.002	0.002	0.001	0.001
	[0.003]	[0.003]	[0.001]	[0.001]
Operating Revenues, ln	0.001	0.000	-0.002	-0.002
	[0.005]	[0.005]	[0.002]	[0.002]
Patent (lag)			0.711***	0.710***
			[0.053]	[0.053]
Firm and Year F.E.	YES	YES	YES	YES
Obs.	18,436	18,436	13,272	13,272
No. of individuals	2,435	2,435	2,241	2,241
No. of instruments			71	72
AR1 (p-value)			0.000	0.000
AR2 (p-value)			0.064	0.061

*** p<0.01, ** p<0.05, * p<0.1; robust standard errors are reported in brackets

Table 12. OLS TWO WAY FIXED EFFECTS – Exclusion of French and German DFIs

	(1)	(2)	(3)	(4)
	Whole sample		PSM sample	
	Exclusion of French DFIs			
PostDeal	0.018***	0.018***	0.016*	0.016*
	[0.003]	[0.003]	[0.008]	[0.008]
PostDeal * DFIbacked	0.088***		0.055**	
	[0.021]		[0.023]	
PostDeal * DFIonly		0.032		-0.002
		[0.030]		[0.032]
PostDeal * DFIpartner		0.119***		0.086***
		[0.028]		[0.030]
Obs.	85,143	85,143	17,018	17,018
	Exclusion of German DFIs			
PostDeal	0.019***	0.019***	0.022**	0.022**
	[0.003]	[0.003]	[0.009]	[0.009]
PostDeal * DFIbacked	0.061***		0.028	
	[0.016]		[0.019]	
PostDeal * DFIonly		0		-0.038
		[0.022]		[0.025]	
PostDeal * DFIpartner		0.090***		0.059**
		[0.021]		[0.023]
Obs.	87,276	87,276	18,370	18,370

*** p<0.01, ** p<0.05, * p<0.1; robust standard errors are reported in brackets

Note: usual controls are applied in the regression but omitted from the table for clarity purposes

Table A.1. List of European DFIs

Multilateral Development Financial Institutions	Country Code
BLACK SEA TRADE & DEVELOPMENT BANK	II
COUNCIL of EUROPE DEVELOPMENT BANK	II
EUROPEAN BANK FOR RECONSTRUCTION & DEVELOPMENT EBRD BERD	II
EUROPEAN COMPANY FOR THE FINANCING of RAILROAD ROLLING STOCK SA	II
EUROPEAN INVESTMENT BANK EIB	II
EUROPEAN INVESTMENT FUND	II
INTERNATIONAL BANK FOR ECONOMIC CO-OPERATION – IBEC	II
NORDIC ENVIRONMENT FINANCE CORPORATION	II
NORDISKA INVESTERINGSBANKEN	II

National and Sub-National Development Financial Institutions	Country Code
AUSTRIA WIRTSCHAFTSSERVICE GESELLSCHAFT MIT BESCHRAENKTER HAFTUNG	AT
OESTERREICHISCHE ENTWICKLUNGSBANK AG	AT
BELGIAN INVESTMENT COMPANY FOR DEVELOPING COUNTRIES	BE
FONDS DE PARTICIPATION -PARTICIPATIEFONDS -BEITRAGSFONDS	BE
GIMV NV	BE
LIMBURGSE RECONVERSIE MAATSCHAPPIJ	BE
PARTICIPATIEMAATSCHAPPIJ VLAANDEREN	BE
SAMBRINVEST	BE
SOC. BELGE INVESTISSEMENT INTERNAT. BELG. MAATS. INTERNAT. INVESTERING	BE
SOCIETE FEDERALE DE PARTICIPATIONS ET D'INVESTISSEMENT SA/NV	BE
SOCIETE REGIONALE D'INVESTISSEMENT DE WALLONIE	BE
BULGARIAN DEVELOPMENT BANK AD	BG
SIFEM AG	CH
CESKOMORAVSKA ZARUCNI A ROZVOJOVA BANKA A.S.	CZ
CZECH EXPORT BANK	CZ
BREMER AUFBAU-BANK GMBH	DE
DEG - DEUTSCHE INVESTITIONS-UND ENTWICKLUNGSGESELLSCHAFT MBH	DE
HAMBURGISCHE INVESTITIONS- UND FOERDERBANK	DE
INVESTITIONS- UND STRUKTURBANK RHEINLAND-PFALZ (ISB)	DE
INVESTITIONS-UND FORDERBANK NIEDERSACHSEN GMBH	DE
INVESTITIONSBANK BERLIN	DE
INVESTITIONSBANK DES LANDES BRANDENBURG	DE
INVESTITIONSBANK SACHSEN-ANHALT	DE
INVESTITIONSBANK SCHLESWIG-HOLSTEIN	DE
KFW BANKENGRUPPE	DE
LANDESKREDITBANK BADEN-WUERTTEMBERG – FORDERBANK	DE
LANDWIRTSCHAFTLICHE RENTENBANK	DE
LFA FORDERBANK BAYERN	DE
NRW.BANK	DE
SAARLAENDISCHE INVESTITIONSKREDITBANK AG	DE
SAECHSISCHE AUFBAUBANK FORDERBANK	DE
THURINGER AUFBAUBANK	DE
WIRTSCHAFTS- UND INFRASTRUKTURBANK HESSEN	DE
INVESTERINGSFONDEN FOR UDVIKLINGSLANDE (IFU)	DK
KOMMUNEKREDIT	DK
FUND KREDEX	EE
COFIDES	ES
EMPRESA NACIONAL DE INNOVACION S.M.E, SA	ES
INSTITUT CATALA DE FINANCES	ES
INSTITUTO DE CREDITO OFICIAL	ES
INSTITUTO VALENCIANO DE FINANZAS	ES
SEPI DESARROLLO EMPRESARIAL SA SME.	ES
SOCIEDAD DE DESARROLLO DE NAVARRA SL.	ES
FINNISH FUND FOR INDUSTRIAL COOPERATION LTD	FI
FINNVERA PLC	FI
KOUVOLA INNOVATION OY	FI
MUNICIPALITY FINANCE PLC	FI
AGENCE FRANCAISE DE DEVELOPPEMENT	FR
BPIFRANCE	FR
CAISSE DE GARANTIE DU LOGEMENT LOCATIF SOCIAL	FR
CAISSE DES DEPOTS ET CONSIGNATIONS	FR
INSTITUT REGION DEVELOP INDUST MIDI PYR	FR

QUALIUM INVESTISSEMENT	FR
SADEPAR	FR
SFIL	FR
SOCIETE DE PROMOTION ET DE PARTICIPATION POUR LA COOPERATION ECONOMIQUE SA	FR
BRITISH BUSINESS BANK PLC	GB
CDC GROUP PLC	GB
EXPORT CREDITS GUARANTEE DEPARTMENT	GB
SCOTTISH ENTERPRISE	GB
CROATIAN BANK FOR RECONSTRUCTION & DEVELOPMENT	HR
CORVINUS RT	HU
HUNGARIAN EXPORT-IMPORT BANK PRIVATE LTD	HU
MFB HUNGARIAN DEVELOPMENT BANK PRIVATE LIMITED COMPANY	HU
STRATEGIC BANKING CORPORATION OF IRELAND	IE
BANCA DEL MEZZOGIORNO - MEDIOCREDITO CENTRALE S.P.A	IT
BANCA MEDIOCREDITO DEL FRIULI VENEZIA GIULIA SPA	IT
CASSA DEPOSITI E PRESTITI	IT
FINANZIARIA LIGURE PER LO SVILUPPO ECONOMICO FI.L.S.E. S.P.A.	IT
FINLOMBARDA SPA	IT
FINPIEMONTE S.P.A.	IT
IRFIS - FINANZIARIA PER LO SVILUPPO DELLA SICILIA SPA	IT
MEDIOCREDITO TRENTINO-ALTO ADIGE SPA	IT
SOCIETA' ITALIANA PER LE IMPRESE ALL'ESTERO - SIMEST S.P.A.	IT
VENETO SVILUPPO S.P.A.	IT
UAB VIESUJU INVESTICIJU PLETROS AGENTURA	LT
SOCIETE NATIONALE DE CREDIT ET D'INVESTISSEMENT – SNCI	LU
ATTISTIBAS FINANSU INSTITUCIJA ALTUM AS	LV
INDUSTRIEBANK LIOF	NL
NEDERLANDSE WATERSCHAPSBANK NV	NL
NETHERLANDS DEVELOPMENT FINANCE COMPANY	NL
EKSPORTFINANS ASA	NO
KOMMUNALBANKEN AS	NO
NORFUND	NO
BANK GOSPODARSTWA KRAJOWEGO	PL
BANK OCHRONY SRODOWISKA SA - BOS SA	PL
IFD - INSTITUICAO FINANCEIRA DE DESENVOLVIMENTO, SA	PT
EXIMBANK ROMANIA	RO
AB SVENSK EXPORTKREDIT	SE
ALMI FORETAGSPARTNER AKTIEBOLAG	SE
INLANDSINNOVATION AB	SE
KOMMUNINVEST I SVERIGE AB	SE
SWEDFUND INTERNATIONAL AB	SE
SWEDISH EXPORT CREDITS GUARANTEE BOARD	SE
SID - SLOVENE EXPORT AND DEVELOPMENT BANK, INC, LJUBLJANA - SID BANK, INC	SI
EXPORT-IMPORT BANK of THE SLOVAK REPUBLIC - EXIMBANKA SR	SK
SLOVENSKA ZARUCNA A ROZVOJOVA BANKA SPU	SK

Table B.1. Variables' definition

Variable	Source	Description
PostDeal	Zephyr (BvD)	Dummy variable equal to one in the years following the deal year, and zero otherwise
DFIbacked	Zephyr (BvD)	Dummy variable equal to one if the target firm has been financially supported via an equity deal where investors comprise at least one development financial institution (also including direct or second-order subsidiaries that are more than 25 percent owned by a development financial institution), and zero otherwise
DFIonly	Zephyr (BvD)	Dummy variable equal to one if the target firm has been financially supported via an equity deal where investors comprise only development financial institutions (also including direct or second-order subsidiaries that are more than 25 percent owned by development financial institutions), and zero otherwise
DFIpartner	Zephyr (BvD)	Dummy variable equal to one if the target firm has been financially supported via an equity deal where investors comprise both development financial institutions (also including direct or second-order subsidiaries that are more than 25 percent owned by development financial institutions) and other types of investors, and zero otherwise
Patent (applications)	Orbis Intellectual Property (BvD)	Stock of patent applications accumulated until the end of the year of observation, using a constant annual 15 percent depreciation rate (see Griliches, 1990)
Patent (granted & citation-weighted)	Orbis Intellectual Property (BvD)	Stock of granted patents weighted by the number of citations they received after the grant, using a constant annual 15 percent depreciation rate. The calculation of the patent stock is still based on the application year (not the year of the grant)
Size [= Total Assets (ln)]	Orbis (BvD)	Natural logarithm of total assets in EUR thousands
Tangibility	Orbis (BvD)	Ratio of tangible fixed assets to total assets
Intangible intensity	Orbis (BvD)	Ratio of in intangible fixed assets to total assets
Profitability	Orbis (BvD)	Ratio of earning before interests and taxes (EBIT) to total assets
Tangible Assets (ln)	Orbis (BvD)	Natural logarithm of tangible fixed assets in EUR thousands
Intangible Assets (ln)	Orbis (BvD)	Natural logarithm of intangible fixed assets in EUR thousands
Operating Revenues (ln)	Orbis (BvD)	Natural logarithm of operating revenues in EUR thousands
Age	Orbis (BvD)	Difference between observation year and the year of incorporation of the target firm
Listed	Orbis (BvD)	Dummy variable equal to one if the target firm is a publicly traded company, and zero otherwise.

Table B.2. First-stage propensity model (logit)

Dependent variable: DFIbacked dummy	
Size (= Total Assets, ln)	-0.090***
	[0.024]
Tangibility	0.383
	[0.252]
Intangible Intensity	0.478**
	[0.187]
Profitability	-0.120
	[0.087]
Age	-0.090*
	[0.053]
Listed	-0.001
	[0.197]
Patent	0.188***
	[0.048]
Year, Area, Sector Fixed effects	YES
Obs. (deal-level)	8,692

*** p<0.01, ** p<0.05, * p<0.1

Standard errors are reported in brackets

Table B.3. Descriptive statistics (firm-year observations)

	Whole sample (#Obs. = 87,698)			PSM sample (#Obs. = 18,436)		
Variable	Median	Mean	St. Dev.	Median	Mean	St. Dev.
Patent (applications)	0.00	0.34	0.87	0.00	0.56	1.10
Age	10.00	15.87	19.03	10.00	15.11	16.95
Listed	0.00	0.08	0.28	0.00	0.07	0.26
Tangible Assets, ln	5.88	5.78	3.32	5.45	5.48	3.38
Intangible Assets, ln	5.11	4.79	3.59	5.38	4.96	3.40
Operating Revenues, ln	8.95	8.50	2.88	8.46	8.13	2.93

Table B.4. – Alternative controls

(a) OLS FE

Dependent variable: Patent (applications)

	Whole Sample		PSM Sample	
	(1)	(2)	(3)	(4)
PostDeal	0.015***	0.015***	0.013	0.013
	[0.003]	[0.003]	[0.008]	[0.008]
PostDeal * DFIbacked	0.058***		0.027	
	[0.016]		[0.019]	
PostDeal * DFIonly		0.002		-0.027
		[0.022]		[0.024]
PostDeal * DFIpartner		0.084***		0.052**
		[0.021]		[0.023]
Age	0.005***	0.005***	0.009***	0.009***
	[0.001]	[0.001]	[0.002]	[0.002]
Listed	0.028*	0.028*	0.032	0.034
	[0.016]	[0.016]	[0.023]	[0.023]
Tangibility (lag)	-0.016	-0.016	-0.054	-0.053
	[0.012]	[0.012]	[0.034]	[0.034]
Intangibility (lag)	0.012	0.012	0.019	0.018
	[0.011]	[0.011]	[0.027]	[0.027]
Profitability (lag)	-0.031***	-0.031***	-0.059***	-0.057***
	[0.004]	[0.004]	[0.010]	[0.010]
Total Assets, ln (lag)	0.028***	0.028***	0.041***	0.041***
	[0.002]	[0.002]	[0.006]	[0.006]
Firm and Year F.E.	YES	YES	YES	YES
Obs.	86,109	86,109	18,416	18,416
No. of individuals	13,253	13,253	2,435	2,435

(b) DIFF-GMM

Dependent variable: Patent (applications)

	Whole Sample		PSM Sample	
	(3)	(4)	(3)	(4)
PostDeal	0.006***	0.006***	0.003	0.003
	[0.002]	[0.002]	[0.005]	[0.005]
PostDeal * DFIbacked	0.020***		0.018***	
	[0.004]		[0.006]	
PostDeal * DFIonly		0.012		0.011
		[0.007]		[0.010]
PostDeal * DFIpartner		0.024***		0.021***
		[0.005]		[0.007]
Age	-0.002***	-0.002***	-0.003**	-0.003**
	[0.000]	[0.000]	[0.001]	[0.001]
Listed	0.008	0.008	0.011	0.011
	[0.009]	[0.009]	[0.028]	[0.028]
Tangibility (lag)	-0.008	-0.008	-0.023	-0.022
	[0.006]	[0.006]	[0.016]	[0.016]
Intangibility (lag)	0.009**	0.009**	0.013	0.013
	[0.005]	[0.005]	[0.011]	[0.011]
Profitability (lag)	-0.006***	-0.006***	-0.010**	-0.009**
	[0.002]	[0.002]	[0.004]	[0.004]
Total Assets, ln (lag)	0.010***	0.010***	0.016***	0.016***
	[0.001]	[0.001]	[0.002]	[0.002]
Patent (lag)	0.627***	0.627***	0.644***	0.643***
	[0.016]	[0.016]	[0.035]	[0.035]
Firm and Year F.E.	YES	YES	YES	YES
Obs.	58,780	58,780	13,257	13,257
No. of individuals	10,750	10,750	2,241	2,241
No. of instruments	72	72	72	72
AR1 (p-value)	0.000	0.000	0.000	0.000
AR2 (p-value)	0.192	0.192	0.270	0.270

*** p<0.01, ** p<0.05, * p<0.1; robust standard errors are reported in brackets

Table B.5. ZINB model

Dependent variable: Patent (applications)				
	Whole Sample		PSM Sample	
	(1)	(2)	(3)	(4)
PostDeal	0.493***	0.496***	0.507***	0.497***
	[0.050]	[0.050]	[0.095]	[0.097]
DFIbacked	0.234**		-0.242**	
	[0.095]		[0.101]	
PostDeal * DFIbacked	0.272**		0.272**	
	[0.117]		[0.130]	
DFIonly		0.079		-0.497*
		[0.282]		[0.282]
PostDeal * DFIonly		0.035		-0.137
		[0.321]		[0.348]
DFIpartner		0.281***		-0.197**
		[0.079]		[0.092]
PostDeal * DFIpartner		0.340***		0.382***
		[0.105]		[0.119]
Age	0.004***	0.004***	-0.000	-0.002
	[0.001]	[0.001]	[0.003]	[0.002]
Listed	1.531***	1.581***	2.030***	2.239***
	[0.080]	[0.082]	[0.150]	[0.162]
Tangible Assets, ln	0.108***	0.109***	0.197***	0.197***
	[0.012]	[0.012]	[0.019]	[0.020]
Intangible Assets, ln	0.100***	0.102***	0.055***	0.058***
	[0.008]	[0.008]	[0.010]	[0.010]
Operating Revenues, ln	0.032***	0.034***	-0.027	-0.021
	[0.011]	[0.011]	[0.018]	[0.018]
Inflate				
PostDeal	-0.533***	-0.529***	-0.756***	-0.801***
	[0.074]	[0.074]	[0.185]	[0.192]
DFIbacked	-0.493***		-0.422**	
	[0.147]		[0.167]	
PostDeal * DFIbacked	-0.216		0.399*	
	[0.187]		[0.206]	
DFIonly		-0.441		-0.107
		[0.384]		[0.335]
PostDeal * DFIonly		-0.289		0.138
		[0.433]		[0.417]
DFIpartner		-0.516***		-0.618***
		[0.152]		[0.184]
PostDeal * DFIpartner		-0.215		0.410*
		[0.197]		[0.226]
Age	-0.014***	-0.014***	-0.037***	-0.039***
	[0.002]	[0.002]	[0.005]	[0.005]
Tangible Assets, ln	-0.541***	-0.519***	-1.833***	-1.672***
	[0.111]	[0.112]	[0.264]	[0.271]
Intangible Assets, ln	-0.096***	-0.097***	-0.027	-0.027
	[0.015]	[0.015]	[0.036]	[0.037]
Operating Revenues, ln	-0.069***	-0.067***	-0.212***	-0.211***
	[0.012]	[0.012]	[0.014]	[0.015]
Year, Area, Sector Fixed effects	YES	YES	YES	YES
Obs.	87,698	87,698	18,436	18,436

*** p<0.01, ** p<0.05, * p<0.1; robust standard errors are reported in brackets

Table B.6. Granted & Citation-weighted Patents (whole sample)

Dependent variable: Patent (granted & citation-weighted)				
	OLS FE		DIFF-GMM	
	(1)	(2)	(3)	(4)
PostDeal	0.015***	0.015***	0.008***	0.008***
	[0.005]	[0.005]	[0.003]	[0.003]
PostDeal * DFIbacked	0.069***		0.014*	
	[0.024]		[0.007]	
PostDeal * DFIonly		-0.025		-0.018
		[0.035]		[0.012]
PostDeal * DFIpartner		0.112***		0.029***
		[0.030]		[0.009]
Age	0.012***	0.012***	0.000	0.000
	[0.001]	[0.001]	[0.001]	[0.001]
Listed	0.043	0.044	0.005	0.005
	[0.028]	[0.028]	[0.015]	[0.015]
Tangible Assets, ln	0.005***	0.005***	0.003***	0.003***
	[0.002]	[0.002]	[0.001]	[0.001]
Intangible Assets, ln	0.002*	0.002	0.001**	0.001**
	[0.001]	[0.001]	[0.001]	[0.001]
Operating Revenues, ln	0.006***	0.006***	0.001	0.001
	[0.002]	[0.002]	[0.001]	[0.001]
Patent (lag)			0.691***	0.690***
			[0.025]	[0.025]
Firm and Year F.E.	YES	YES	YES	YES
Obs.	87,698	87,698	59,471	59,471
No. of individuals	13,695	13,695	10,986	10,986
No. of instruments			71	72
AR1 (p-value)			0.000	0.000
AR2 (p-value)			0.120	0.116

*** p<0.01, ** p<0.05, * p<0.1; robust standard errors are reported in brackets

FIGURES

Figure 1. Propensity score distribution for treated and control groups before and after matching.

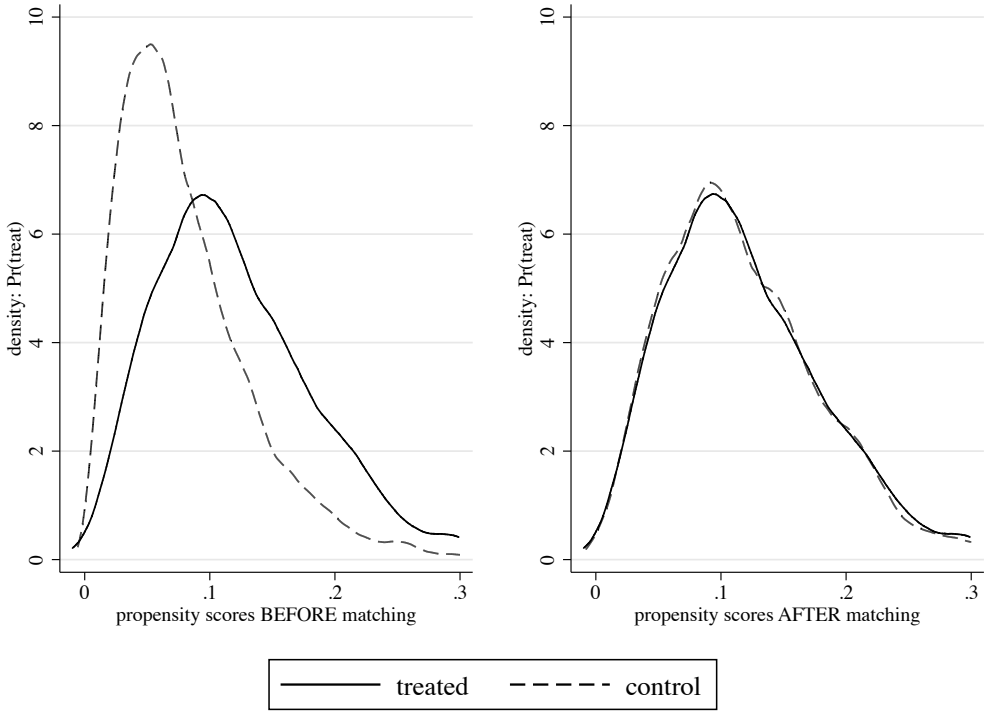

Figure 2. Panel event study design