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Andrea Bellucci[a,b], Serena Fatica[b,c], Aliki Georgakaki[c], Gianluca Gucciardi[d], Simon Letout[c] and Francesco Pasimeni[c,e]

[a]Department of Economics, University of Insubria, Varese, Italy; [b]Money and Finance Research Group (MoFir), Ancona, Italy; [c]European Commission - Joint Research Centre, Petten, Netherlands; [d]Department of Economics, Management and Statistics, University of Milano-Bicocca, Milan, Italy; [e]School of Innovation Sciences, Eindhoven University of Technology, Eindhoven, Netherlands

ABSTRACT

This paper explores the role of green innovation in attracting venture capital (VC) financing. We use a unique dataset that matches information on equity transactions, companies' balance sheet variables and data on patented innovation at the firm level over the period 2008–2017. Taking advance of a novel granular definition of green innovative activities that tracks patents at the firm level, we show that green innovators are more likely to receive VC funding compared to other equity financing than firms without green patents. Likewise, a larger share of green vs. non-green patents in a firm's patent portfolio increases the probability of receiving VC finance with respect to other equity. Robustness checks and extensions tackling several dimensions of heterogeneity confirm the attractiveness of green patenting for VC investment.

KEYWORDS
Venture Capital; Sustainable Finance; Finance for Innovation; Equity Financing; Green ventures; Green technology; Patents

JEL Classification
G24; M13; M21; O35; Q55

1. Introduction

The commitment to climate neutrality by 2050 and to the other ambitious environmental goals set at the international level, such as the European Green Deal, involve structural economic changes and significant technological innovation, which implies both the creation of new products and processes and their diffusion and application. The International Energy Agency (International Energy Agency 2021) projects that, in 2050, almost 50% of CO2 emissions reductions in the net-zero scenario come from technologies currently at demonstration or prototype stage.

The financial effort required to move towards less environment- and resource-intensive economies and societies is equally unprecedented. Already in 2016, the World Bank's International Finance Corporation estimated investment opportunities from the green transition worth about USD 23 trillion until 2030 (International Finance Corporation 2016). As part of this, the IEA documents that the investment in energy systems, particularly in renewables, has risen to USD 820 billion in 2021. Alignment with the target of net-zero emissions by 2050 still requires tripling this figure by 2030. At the

CONTACT Serena Fatica serena.fatica@ec.europa.eu European Commission, Joint Research Centre (JRC), Via E. Fermi, 2749, Ispra, VA 21027, Italy

European level, the 2050 net-zero target calls for an increase in energy-related investments worth € 350 billion annually in the period 2021–2030 compared to previous decade.

The sheer magnitude of the investment needs calls for mobilising private capital on a massive scale. In this context, equity financing can play an important role. In this paper, we explore the nexus between equity financing and firms' green innovation, focusing in particular on the potential for green patents to attract Venture Capital (VC) funding.

In general, venture capitalists have a recognised natural propensity to fund firms with high potential but risky growth trajectories and returns (Gompers and Lerner 2004). Moreover, their ability to rapidly shift investments and fund new ventures in response to market prospects and signals (Bellucci et al. 2023; Gompers et al. 2021; Howell et al. 2020) makes them a potential source of finance even in the short term. The strong link between VC and innovation is already well documented in the literature (e.g. Florida and Kenney 1988; Kortum and Lerner 2001; Lerner 2002; Da Rin and Penas 2007; Hall and Lerner 2010; Hirukawa and Ueda 2011; Arvanitis and Stucki 2014; Faria and Barbosa 2014; Bernstein, Giroud, and Townsend 2016; among others). While imperfections and frictions in capital markets discourage investments in research and development, given the important asymmetric information inherent in these activities (Carpenter and Petersen, 2002; Hall 2002), their high risk-return profile is typically very attractive to VC finance. In this context, patents can mitigate financing constraints and act as a signalling device to investors. As a result, much of the research on the patenting-finance relationship has focused on VC financing (Conti, Thursby, and Rothaermel 2013; De Vries et al. 2017; Farre-Mensa, Hegde, and Ljungqvist 2020; Haeussler, Harhoff, and Mueller 2014; Heger and Hussinger 2017; Hoenen et al. 2014; Hoenig and Henkel 2015; Kaplan and Stromberg 2001; Mann and Sager 2007; Munari and Toschi 2015; Popov and Roosenboom 2012; Sichelman and Graham 2010; Zhang, Guo, and Sun 2019).[1]

The specific nature of green innovative ventures and its relationship with equity finance is still an open question. The relatively high capital intensity of green ventures and the fact that green deals take longer to reach the maturity phase pose challenges to the traditional VC business model (see e.g. Criscuolo and Menon 2015; Demirel et al. 2019; Zhang, Jing, and Wang 2015).[2] Moreover, green innovators are involved in patenting activities that are very complex from a technological standpoint, as documented by the fact that green patents have more general applications (Amore and Bennedsen 2016) and receive citations from a wider array of technological classes than other types of patents (Popp and Newell 2012). These distinctive features of green patents have important implications also for firm organisation, such as corporate governance, in that worse governed firms generate fewer green patents relative to all their innovations (Amore and Bennedsen 2016; Demirel et al. 2019). Green ventures entail both technical and managerial complexity, because of the nature of the environmental technologies and the infant

[1] Another strand of the literature analyzes the impact of VC financing on firms' patenting activities. It provides mixed evidence on the relationship between VC financing and firms' patent filing (Baum and Silverman 2004; Cao and Hsu 2011; Dong et al. 2021; Engel and Keilbach 2007; Kortum and Lerner 2000). In contrast, the ability of VC funds to contribute positively to aggregate growth by enabling innovation is increasingly apparent (Akcigit et al. 2019; Bernstein, Giroud, and Townsend 2016; Kortum and Lerner 2000).

[2] A paradigmatic example are deep-tech start-ups, which build on scientific knowledge and are characterised by long R&D cycles and untested business models. They typically rely on large capex investments in pilot plants for new technologies to be able to scale their revenues.

stage of the sector in terms of commercialisation and market acceptance, and, thus, may be exposed to higher risk of market exit. These features may reduce their attractiveness for VC investors compared to other high-tech ventures (Ghosh and Nanda 2010), hinting at other types of equity funding (e.g. Private Equity and Growth Equity) being potentially a better fit for green innovative firms. VC financing is inherently different from other types of equity financing along several dimensions, such as the stage of investment, the invested amount, the reasons underlying the provision of capital, the investors' strategic objectives and the nature of their involvement in the management of the backed-company (see, for instance, Cumming and Vismara (2017) and Drover et al. (2017), among others). For instance, while VC is one of the most relevant sources of funding for new ventures, private equity funds represent a natural financing source for firms pursuing capital-intensive and risky investment strategies (Breuer and Pinkwart 2018). In highlighting significant differences in the investment strategies of venture capitalists and other equity investors (Block et al. 2019), the literature has also found that private equity funds are more likely to finance sufficiently mature and cash-flow-dependent companies (Bertoni, Ferrer, and Martí 2013). At the same time, compared to VC, equity crowdfunding allows the entrepreneur to retain more influence, by substituting a single (or a few) major outside investor with a large number of smaller ones (Drover et al. 2017). Moreover, behavioural differences emerge also among the different types of venture capital investors, and between US and Europe-based funds (Bertoni, Colombo, and Quas 2015).

Against this background, the potential venture capital funding to finance green innovation remains an empirical question. We tackle it using a unique dataset that matches information on VC and other equity deals with company level financial and patent data over the period 2008–2017. The classification between green and non-green patents is based on the methodology developed by the European Commission's Joint Research Centre (JRC) to build indicators of global innovative activity in clean energy technologies (Fiorini et al. 2017; Pasimeni 2019; Pasimeni, Fiorini, and Georgakaki 2019; Pasimeni, Fiorini, and Georgakaki 2021). This methodology improves on alternative empirical approaches that classify firms' activities as green exclusively based on the description of their business operations (e.g. Mrkajic, Murtinu, and Scalera 2019).

Using a probabilistic regression model, we explore whether green patenting increases the likelihood that a firm receives VC funding compared to other equity finance. We find that having a green patent is associated with up to approximately 20% higher probability of raising VC relative to other equity finance, all other things – including a set of control variables proxying for the characteristics of the target ventures – being equal. Likewise, a larger share of green vs. non-green patents in a firm's patent portfolio increases the probability of receiving VC funds compared to other types of equity. Our baseline results are robust to the use of a matched sample of firms to address endogeneity concerns, and to a number of further checks to account for potential non-linearities and cross-country differences among VCs and innovation ecosystems. Further, we uncover some heterogeneity in the impacts in terms of type of VC investor, such as Corporate Venture Capital (CVC), Business Angel (BA) or Independent Venture Capital (IVC), and financing stage, i.e. early or later. Overall, our findings corroborate the view that green patenting, in addition to broader innovation activities, is a distinctive important driver of VC with respect to other equity funding.

Our work relates and contributes to the literature that explores the innovation-financing nexus. As a first contribution, our paper sheds light on the attractiveness of green patents for VC investors in Europe. Our empirical findings suggest important qualifications to the arguments that question the adequacy for VC to finance green innovation (Ghosh and Nanda 2010), particularly those based on the narrative accounts of the cleantech boom-bust cycle in the US (Gaddy et al. 2017). At the very least, our results caution against any generalisation in this assessment, given the differences in investment strategies across VC investor types and geographies (Bertoni, Colombo, and Quas 2015).

Secondly, our paper adds to the strand of the literature that investigates the signalling role of patents for risk finance (see, e.g. Hall 2019; Hoenig and Henkel 2015; Hottenrott, Hall, and Czarnitzki 2017). In this context, our results highlight the specific role of green patents in the context of general patenting activities. The distinctive features of green innovation discussed above make the topic worth exploring and our analysis particularly relevant, as they may potentially invalidate the results obtained in the literature on the general population of patents.

Third, from a methodological standpoint, our granular definition of green innovative activities that tracks and classifies patents at the firm level improves on the extant literature that employs aggregate data on green sectors (Criscuolo and Menon 2015; Mrkajic, Murtinu, and Scalera 2019). In fact, when we check our results against a different definition of green ventures, based on an aggregate NACE2 sectoral classification, we do not find a significant link between VC and green activities, in line with Mrkajic, Murtinu, and Scalera (2019). This suggests that the relevant green characteristics of firms are patent-specific and not sector-specific.

By documenting the attractiveness of green patenting for VC investment, our findings suggest that this type of equity finance can play an important role in fostering green innovation. This, in turn, can generate positive externalities in the form of knowledge spillovers and thus facilitate the adoption and diffusion of environmental technologies, and, ultimately, help achieve the low-carbon targets and facilitate the transition to a greener economy.[3]

The remainder of the paper is structured as follows. Section 2 presents the data and the description of variables, including the definition of green technologies and the methodology used to classify patents. Section 3 describes the empirical strategy, while Section 4 illustrates the main results. Section 5 and 6 report a battery of robustness tests and extensions tackling several dimensions of heterogeneity. Lastly, Section 7 concludes.

2. Data and variables

2.1. Data sources

The empirical analysis builds on a database (hereafter, the *matched DB*) obtained by matching data from three different sources. First, we draw detailed information at the level of individual VC and other equity deals from Dow Jones VentureSource,

[3]For a discussion on the role of innovation in the context of the green transition see Diodato et al. (2022).

a commercial database that provides a information on VC-backed companies, Venture Capital investors and Venture Capital investment transactions, at global level, with breakdown by industry, sector and stage of development.[4] Details on the equity-backed companies include name, addresses, geographical location, website, sector of activity and some financial variables, such as employees, total assets, turnover and total liabilities, at the date of the transaction. Similar data are provided on the investing entities – including the type (e.g. Corporate VC vs Independent VC) – and all the co-investors, if any. Lastly, VentureSource includes information on the deal itself, such as the invested amount, the deal date, the type of investment, notably the round, and the currency of the transaction.[5] For the purpose of this study, we exploit the VentureSource database considering venture-backed companies as the primary target of analysis. VentureSource also includes data for several other forms of equity investments (and related equity-backed companies) such as Angel investments, Private Equity, and Crowdfunding. These are potential candidates for the control group with respect to which VC-backed firms are compared. In the analysis, we focus on companies located in EU-27 and the United Kingdom in the period 2008–2017.

To overcome some limitations of VentureSource,[6] we match the equity-backed companies with financial information retrieved from the Orbis database, provided by Moody's Bureau Van Dijk. Orbis contains financial data from firms' profit and loss accounts and balance sheets gathered from business registers, credit bureaus, statistical offices, and company annual reports for each accounting year. The raw information is harmonised to enable meaningful cross-country comparison.[7] Finally, we obtain bibliographical and legal event patent data from Patstat. Patstat is the patent statistical database created and maintained by the European Patent Office (EPO), and collects patent data directly from the EPO itself and from other sources, such as national and supranational patent authorities, across leading industrialised and developing countries. Despite its global coverage, the incomplete provision of data generates lack of accuracy and completeness, which requires a preliminary cleaning procedure before processing the data in order to avoid elaboration of misleading information (Pasimeni 2019).

The classification between green and non-green patents is based on the methodology developed by the European Commission's Joint Research Centre (JRC) to derive indicators of global innovative activity in clean energy technologies (Fiorini et al. 2017; Pasimeni 2019; Pasimeni, Fiorini, and Georgakaki 2019; Pasimeni, Fiorini, and Georgakaki 2021). All patent documents relevant to a distinct invention (e.g. patent applications to multiple authorities) are grouped under the same family, as a reliable

[4]Previous studies already provided a detailed overview of VentureSource (Kaplan, Strömberg, and Sensoy 2002; Nepelski, Piroli, and De Prato 2016) and a comparison with other commercial databases (e.g. Thomson Venture Economics and Crunchbase) for a purpose similar to that of the current investigation. In particular, they found that VentureSource is a more comprehensive data source offering longitudinal and standardised information on VC deals, with more detailed information on financed and financing entities. Along these lines, Kuckertz, Berger, and Gaudig (2019) state that VentureSource is a comprehensive data source, particularly when looking at VC deals completed in the United States and Europe.

[5]In the text, we refer to the number of deals (and related amounts) including both disclosed and undisclosed transactions. We alternatively refer to VC deals as VC transactions.

[6]VentureSource does not provide, for instance, the historical series of financial information of VC-backed firms for the years before and after the VC transaction and a standard classification of the VC-backed firms' industry.

[7]Evidence of the advantage in using Orbis over similar commercial databases is already described in Kalemli-Ozcan et al. (2015). In particular, the authors state that Orbis provides harmonised balance sheets and profit and loss data with a significant coverage of private companies, together with a more detailed industry classification (NACE 4-digit codes).

proxy of one invention. Patents in green technologies are detected via the Y02 and Y04 schemes of the Cooperative Patent Classification (CPC) that specifically tag patents related to climate change mitigation technologies. Therefore, the technology tags assigned to patent applications allow us to pin down firms' inventive activity in the green technology area.

2.2. The matched database

The process for the creation of the *matched DB* has been performed in two steps. First, we matched data from VentureSource and Orbis. In the absence of a common unique identifier, entities in the two databases have been matched using univocal variables available in both databases, such as the company name, the web and email addresses, and the telephone and fax numbers. The matching between VentureSource and Orbis associates for each company the contract terms of the deal, i.e. the amount, the deal date, the type of investment or the funding round, the currency and the name and geographical location of the investor(s), with the financial information of the target company – notably total assets, total debt, turnover, number of employees, industry – available from Orbis.[8] The dataset resulting from the matching between VentureSource and Orbis includes 11,546 observed companies.

Next, we need to extract which firms from the VentureSource-Orbis merged dataset have an inventive activity, and, if so, whether or not that extends also to green technologies. To this purpose, in the second step, the data is further matched with the information on patents. A major obstacle in the use of patent data is the disambiguation of individuals and institutions (Morrison et al., 2017). This is because patent documents do not contain firm identification codes. Likewise, patent databases may include multiple entries and identifiers for the same firm as an applicant. When matching with firm level data, typical problems arise from variations in the spelling of a person's or institution's name (including typos and misspellings), from variations in the way names appear in two or several datasets (in many cases caused by different naming conventions) or from the problem of consolidating firm subsidiaries in groups. The goal of disambiguation is to link and consolidate all these alternate spellings of institutional or individual names without incorrectly including similar names referring to different entities. To this end, we apply a simple approach that matches companies from the VentureSource-Orbis dataset, with companies as defined by the cleaning and grouping in the JRC patent dataset (Pasimeni and Fiorini 2017). The latter uses data from the OECD HAN (Harmonised patents Applicant's Names) database[9] as an input to the patent-based methodology proposed in Pasimeni, Fiorini, and Georgakaki (2021). The name and country of location of the company are the only attributes common in the two datasets. Therefore, our procedure (i) standardises the company names in both datasets and (ii) for each company name in the VentureSource-Orbis dataset identifies and validates a unique match in the

[8]We should acknowledge that Orbis does not exactly cover the same firms included in VentureSource, and vice versa. In addition, despite its large coverage, Orbis does not provide financial statements for some young SMEs provided by VentureSource. Indeed, many SMEs do not disclose a financial report of their business on first stages of activity, and some of them may end their business after having received early stages financing. Hence, the *matched DB* includes a subset of the information available in VentureSource.

[9]https://www.oecd.org/sti/inno/intellectual-property-statistics-and-analysis.htm

JRC patent dataset. The standardisation of company names uses a dictionary-based approach, consisting of several steps derived from Thoma et al. (2010) to facilitate the matching and its validation. A fuzzy matching algorithm[10] is then used to establish the similarity ratio between the standardised company names from both datasets and to identify for each company from VentureSource-Orbis the best potential match in the JRC patent dataset. The best potential match is the one with the highest similarity ratio, for which the country names are also similar in both datasets.

Out of the 11,546 companies included in the VentureSource-Orbis merged dataset, potential matches are grouped in three categories. Companies in Category 1 (2,089) are matched with a similarity ratio higher than 95 %. These are companies that are matched with the highest confidence and therefore have a patenting activity over the considered period. Companies in Category 2 (8,163) are not matched, that is the fuzzy matching does not return a potential match from the JRC patent dataset in the given country, hence they most likely do not have a patenting activity over the considered period. Lastly, companies in Category 3 (1,294) are matched but with a similarity ratio lower than 95 %. Given that these companies are matched with a lower level of confidence, we cannot have a conclusive answer on whether they had or not a patenting activity over the considered period. In order to ensure representativeness of the final dataset, we only include Category 1 and 2 companies (i.e. 10,252 companies) and choose to exclude companies in Category 3. For each company having completed any equity transaction in the period 2008–2017 taken from VentureSource-Orbis that is matched with a company from JRC patent dataset, a time series (for the same time period[11]) with the following information is available: (i) the identifiers of the patent families the company has contributed to, allocated to the year of the first patent filling of the family; (ii) for each patent family, dummy variables indicating if the patent family is related to green technologies or non-green technologies (by definition all other technology areas).

Overall, the *matched DB* between VentureSource, Orbis and Patstat contains 11,748 observations – with the identifier being the single VC/other equity transaction completed over the period 2008–2017 – of which 2,240 are related to firms holding patents (Category 1) and 9,508 to firms without any patent (Category 2). Our investigation also requires relevant information about the characteristics of the equity-backed enterprises, included as control variables to take into account unobserved heterogeneity.[12]

2.3. Dependent and control variables

Our aim is to analyse whether, within the pool of equity-backed firms, those that have registered a green patent have a higher probability of raising Venture Capital financing respect to other sources of equity finance than firms which either hold non-green patents only or do not hold any patents. To test whether firms with green patents have higher probability of raising VC investments compared to other equity finance, we construct our

[10]https://github.com/seatgeek/fuzzywuzzy

[11]Patent applications are published between 18 and 30 months after they are actually filed. Patent data statistics provided by the autumn version of Patstat 2019 are therefore not complete for the year 2017 (Pasimeni and Georgakaki 2020). This implies that some Category 2 companies may have contributed to a new patent family later in 2017 and be confirmed as Category 1 companies in future Patstat vintages.

[12]Not for all firms in our *matched* DB relevant information from balance sheets is available. This reduces the number of observations for our baseline estimations to 5,775, as further explained in section 2.3.

dependent variable as a dummy indicator, *VC*, that, for each equity transaction *j* observed for firm *i*, is equal to one if the deal is for VC finance, and zero otherwise. We focus on deals occurring in the period 2008–2017. The definition of VC and the classification of VC investment types is the one provided by VentureSource. Throughout this work, we adopt a *stringent* definition of Venture Capital and our variable, *VC*, includes firms only raising the following funding types: Seed, all VC funding rounds (from 1st to 9th) and VC later rounds.[13] Conversely, the other equity finance category includes all the other equity transactions of the following types: Private Equity, Growth Equity, Accelerator, Crowdfunding, Business Angel (BA), Corporate Venture Capital (CVC), Venture Recapitalization, and Venture Leasing. For the sake of robustness. In line with similar approaches in the literature (see, e.g. Bellucci, Gucciardi, and Nepelski 2021) we adopt, in some other specifications, a broader definition of VC investments, *VC broad*, extending the stringent definition also to other type of equity finance, that is Accelerator, Business Angel investments, Venture Recapitalization, Venture Leasing, and Corporate Venture Capital (CVC).

To explore the nexus between venture capital financing and firms' green patenting activities, we first classify firms based on the presence of green patents in their patent's portfolio. The distinction between green and non-green patents is based on the methodology developed by the European Commission's JRC (Pasimeni, Fiorini, and Georgakaki 2021) to derive indicators of global innovative activity in clean energy technologies. Operationally, we define an indicator variable (*GreenPat*) that takes the value of one if the firm holds at least one green patent according to our classification at the year of VC (or other equity) funding, and zero if the firm does not have any green patents. In a similar vein, we build another indicator variable (*OtherPat*) that takes the value of one if the firm's patents portfolio contains non-green patents only at the year of the funding, and zero otherwise.

Several firm characteristics could be related to both the likelihood of receiving VC funding and the likelihood of being a (green) innovator. To ensure the estimated effects of the firms' patenting activities are not driven by such confounding factors, we include several control variables in our econometric analysis. First, we consider firm size, proxied using firm's total assets (*Assets*), available from the balance sheets (Orbis). Then, we include the age of the firm at the time of the VC investment (*Age*), generated as the difference between the funding year and the date of incorporation. Next, to account for the firm capital structure, we focus on a measure of indebtedness (*Leverage*), defined as the ratio between long term debt plus loans over total assets. We also consider the research and development activities carried out by the firms (*R&D*). Specifically, we build an indicator that takes the value of one if the firm develops any research and development activity as reported in its balance sheet, and zero otherwise.[14] To minimise

[13]Seed refers to funding rounds for research activities or for the assessment and development of initial concepts prior to the start-up phase. VC funding rounds from 1st to 9th refer to the financing of companies at different stages of funding after the seed phase. Later stages refer to all financing rounds subsequent to the 9th round and are provided for the expansion of more established and operating companies.

[14]In line with other studies on VC financing (e.g. Lahr and Mina 2016), we use the presence of R&D expenditure as a predictor for the firm's propensity to get equity financing. The choice of a dichotomous variable minimises concerns for measurement error stemming from the quality of the variable for R&D expenditure in Orbis, particularly for the small and medium-sized firms. In general, standard accounting data might not accurately report the number and costs of employees who are dedicated to R&D activities or the timing of R&D costs.

Table 1. Summary Statistics.

	Total			Green Patents			Non-green Patents			No Patents		
Variables	*Obs.*	*Avg*	*SD*	*Obs.*	*Avg*	*SD*	*Obs.*	*Avg*	*SD*	*Obs.*	*Avg*	*SD*
VC	5,775	0.38	0.49	242	0.49	0.50	977	0.47	0.50	4,556	0.35	0.48
VC broad	5,775	0.44	0.50	242	0.52	0.50	977	0.51	0.50	4,556	0.42	0.49
Assets	5,775	7.99	2.18	242	8.5	2.16	977	7.97	1.98	4,556	7.96	2.22
Age	5,775	1.83	0.91	242	1.93	0.80	977	1.89	0.83	4,556	1.81	0.93
Leverage	5,775	0.22	0.34	242	0.27	0.37	977	0.27	0.38	4,556	0.21	0.33
R&D	5,775	0.02	0.13	242	0.07	0.25	977	0.04	0.19	4,556	0.01	0.10

Notes: The table provides descriptive statistics for the variables used in the analysis for all transactions and for the groups of transactions with firms with green patents, for firms without non-green patents and for firms without any patent. *VC* is an indicator variable that takes the value of 1 if the firm receives Venture Capital funding and 0 otherwise (i.e. receives other equity financing). *VC broad* is an indicator variable that takes the value of 1 if the firm receives Venture Capital funding according to our broader definition that also include Business Angel, CVC, Venture Leasing, Venture Recapitalization) and 0 otherwise (i.e. receive other equity financing). *Assets* is the natural logarithm of the total assets of the firm at time *t*-1. *Age* is the natural logarithm of a continuous variable that measures the years since its establishment at time *t*-1. It is expressed in natural logarithm. *Leverage* is the natural logarithm of a continuous variable that measures the firm's financial indebtedness, constructed as the ratio between the firm's Long-term Debt plus Loans scaled by Total Assets at time *t*-1. *R&D* is an indicator variable that takes the value of 1 if the firm develops activities of research and development, and 0 otherwise. The descriptive statistics of the variable *Assets*, *Age*, *Leverage* and *R&D* are reported one year before the financing. The table reports mean and standard deviation of each variable for each group of firms.

potential endogeneity concerns, the control variables *Total Assets, Age, Leverage*, and *R&D* are included with a one-year lag in all our model specifications.

Table 1 reports the descriptive statistics of all the listed variables included in the dataset.[15] Firms with green patenting activities, on average, tend to be larger (in terms of assets), older, more indebted and with higher propensity to invest in R&D activities than firms engaging in non-green patented innovation or without any patenting activities at all.

Our *matched DB* also includes information on the industrial sectors of activity of the firms based on the NACE2 classification, both broad and at 4-digit level, as well as on the country of origin of the firms. We exploit this information to control for sectoral and geographical differences in the econometric analysis. Overall, our baseline sample comprises 5,775 observations, obtained excluding from the larger pool of the overall 11,748 deal-firm observations those companies for which relevant balance sheet information (i.e. assets, leverage, R&D, Age) is not available.

3. Empirical strategy

Our objective is to estimate whether and to what extent the probability of raising a VC investment changes for firms that have been investing in green innovation and have registered a green patent, compared to firms holding non-green patents only or no patents at all. In other words, in line with the literature that considers patenting as a signalling device to mitigate asymmetric information and financial constraints, we test whether green innovation acts as a distinctive signal to the VC market that, ultimately, facilitates firm access to VC funding, with respect to other types of equity finance. Specifically, we estimate several specifications of the following Probit model:

[15]Further description of the variables included in the *matched DB* is available in Table A1 while their correlation matrix is presented in Table A2 of the Appendix.

$$Pr(VC)_{j,i,t} = \alpha + \beta GreenPat_{i,t} + \gamma OtherPat_{i,t} + \delta Controls_{i,t-1} + \varphi_t + \varphi_c + \varphi_s + \varphi_{(c,s)} + _{j,i,t} \tag{1}$$

In Equation 1, *Pr (VC)* is an indicator variable that is equal to one if deal *j* raised by firm *i* at time *t* relates VC finance, and zero otherwise.[16] *GreenPat* is a dummy variable that equals one if the firm holds at least one green patent according to our classification already at the year of VC (or other equity) funding, and zero otherwise. Similarly, *OtherPat* is equal to one if the firm's patents portfolio contains only non-green patents at the year of the funding. To account for any possible unobserved heterogeneity across firms, we include a set of control variables that could have an impact on both the firm probability to raise a VC investment and the likelihood for it to be a green innovator. In particular, the vector *Controls* includes four indicators related to the size (*Assets*), maturity (*Age*), capital structure (*Leverage*), and the attitude towards innovation (*R&D*) of the observed firms. To control for potential shocks occurring in different periods and common to all firms of the sample we add year fixed effects, φ_t. Moreover, to account for cross-sectional heterogeneity across VC markets, we also include a set of country, φ_c, and sector, φ_s, fixed effects. In a tighter specification, we also introduce them interacted, $\varphi_{(c,s)}$, to control for specific characteristics of sectors across countries. Lastly, ε_{jit} is the error term.

In Equation 1, the coefficient β, alongside its associated marginal effect, is the focus of our interest. It represents our estimate of the effect of green innovation on the probability of raising a VC investment. Similarly, the coefficient γ provides information on the effect of non-green innovation on the probability of raising a VC investment. As such, it is also meaningful to compare them to gauge the relative importance of green vs. non-green patenting as signals for VC investors.

Even though the inclusion of controls should allay doubts about the design of the model, the presence of omitted variables could still be a possible source of estimation bias. To mitigate this concern, we follow a methodology developed by Oster (2019) – and recently applied to the VC literature by Murtinu (2021) – to test for the presence of omitted variables. The core idea is that it is possible to infer the relationship between the main regressor (in our case, the dummy for green patent) and potential omitted variables from the relationship between the same regressors and the vector of controls of the model. A cut-off point for the ratio between the variance explained by the unobservables over the variance explained by the observed variables (i.e. the controls) is established. This is referred to as the 'delta' parameter. This estimated parameter should be larger than one to exclude the possibility of an omitted variable bias, since the variance explained by the model should at least be equal to the variance unexplained due to potential omitted variables. When we estimate the delta parameter, we find that it is equal to 1.49, suggesting that unobserved variables should explain approximately 1.5 times the variance explained by the controls in the model to make our estimations null. Therefore, we conclude that the potential presence of omitted variable bias in our data is low.

While the introduction of control variables and fixed effects should mitigate concerns on the specification of the model, an additional potential source of bias for our estimates

[16]The indicator is zero if the firm raises another equity-based financing at year *t*.

Table 2. Balancing test for the matching – Results with NN matching (support 3).

Dep. Variable	VC-backed firms	Other equity-backed	% reduct bias	Difference from other equity-backed firms
Assets	23,387	24,565	90.6	1,178
Age	9.149	8.948	−10.7	−0.201
Leverage	0.440	0.346	31.3	−0.094
R&D	0.039	0.039	100.0	0.000

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. The table shows the mean values in the year before the financing. *Assets* are reported in Millions of euros. The estimation includes the whole set of Fixed Effects. The test is run without replacement and with three nearest neighbours for each treated unit.

may arise from systematic heterogeneity across firms. In other words, VC-backed firms might be systematically different from other equity-backed firms according to some unobserved characteristics. If this is the case, then our econometric estimates would be affected by these confounding factors, which would hamper a clean identification of the effect of green patenting. To eliminate this potential source of bias, we adopt a matching approach. Our goal is to identify a pool of other equity-backed firms that are similar to VC-backed firms along a relevant set of observable characteristics so that the residual difference across these groups is limited to the fact that one group of firms raises a VC, while the other does not. In particular, we implement a propensity score matching (PSM) procedure to build statistically comparable groups of VC-backed and other equity-backed firms. Specifically, we model the probability of a firm receiving VC using the firm country and sector, as well as predetermined financial characteristics, such as assets, age, leverage ratio, investments in R&D, considered at the year before the investment. The matching between firms is based on the Nearest-Neighbor (NN) algorithm.[17] Then, we impose the common support option, that requires that VC-backed firms have comparable other equity-backed firms with similar propensity scores. Starting from 5,775 observations, 1,040 are dropped because of outside support, with the final number of observations in the support being equal to 4,735. Table 2 displays the t-tests for equality of means in the matched sample for the continuous variables included in the PSM logit regression. The t-tests are statistically insignificant, thus suggesting that the matching was successful in that the matched sample is balanced. Therefore, in what follows, we present the baseline results of estimating Equation 1 on both the full and matched samples, while we focus on the matched sample only for the further robustness analyses and extensions.

4. Results

4.1. Baseline results on the full sample

This section presents the baseline results from regression model (1). We first run the model on the full sample of firms. Table 3 reports the coefficient estimates (Panel A) and the associated marginal effects (Panel B). Column (1) reports the benchmark specification that includes the patent indicator variables and the vector of controls at the company level, with one-year lag to

[17]We adopt the nearest-neighbours matching algorithm through the Stata command *psmatch2* developed by Leuven and Sianesi (2003).

Table 3. Baseline model on full sample.

Dep. Variable	(1)	(2)	(3)	(4)	(5)
	VC = 1	VC = 1	VC = 1	VC = 1	VC = 1
Panel A – Probit Estimation					
OtherPat	0.443***	0.437***	0.423***	0.421***	0.482***
	(0.049)	(0.049)	(0.052)	(0.054)	(0.056)
GreenPat	0.570***	0.551***	0.546***	0.509***	0.639***
	(0.092)	(0.093)	(0.096)	(0.097)	(0.102)
Assets	−0.083***	−0.087***	−0.073***	−0.082***	−0.084***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.012)
Age	−0.676***	−0.672***	−0.644***	−0.662***	−0.676***
	(0.026)	(0.026)	(0.028)	(0.029)	(0.031)
Leverage	−0.126**	−0.132**	−0.131**	−0.232***	−0.232***
	(0.053)	(0.053)	(0.055)	(0.060)	(0.061)
R&D	0.233*	0.248*	0.267*	0.226	0.237
	(0.139)	(0.140)	(0.139)	(0.145)	(0.146)
Observations	5,775	5,775	5,775	5,775	5,775
Controls	Yes	Yes	Yes	Yes	Yes
Year	No	Yes	Yes	Yes	Yes
Sector	No	No	Yes	Yes	Yes
Country	No	No	No	Yes	Yes
Sector x Country	No	No	No	No	Yes
Panel B – Marginal Effects					
OtherPat	0.139***	0.136***	0.131***	0.127***	0.142***
	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)
GreenPat	0.179***	0.172***	0.170***	0.154***	0.189***
	(0.029)	(0.029)	(0.030)	(0.030)	(0.030)
Assets	−0.025***	−0.026***	−0.022***	−0.024***	−0.024***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age	−0.206***	−0.204***	−0.196***	−0.196***	−0.197***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Leverage	−0.038**	−0.040**	−0.040**	−0.069***	−0.067***
	(0.016)	(0.016)	(0.017)	(0.018)	(0.018)
R&D	0.071*	0.075*	0.081*	0.067	0.069
	(0.042)	(0.042)	(0.042)	(0.043)	(0.043)
Observations	5,775	5,775	5,775	5,775	5,775
Controls	Yes	Yes	Yes	Yes	Yes
Year	No	Yes	Yes	Yes	Yes
Sector	No	No	Yes	Yes	Yes
Country	No	No	No	Yes	Yes
Sector x Country	No	No	No	No	Yes

Notes: The table reports regression results, on the full sample, of the Probit estimation of Equation 1 in Panel A and associated marginal effects in Panel B. The dependent variable is *VC*, an indicator variable that takes the value of 1 if the firm receives Venture Capital funding and 0 otherwise (i.e. receives other equity financing). *OtherPat* is an indicator variable that takes the value of 1 if the firm's patents portfolio contains non-green patents only at the year of the VC funding and 0 otherwise. *GreenPat* is an indicator variable that takes the value of 1 if the firm holds at least one green patent according to our classification at the year of VC (or other equity) funding, and 0 otherwise. The vector *Controls* includes four indicators related to the size (*Assets*), the experience (*Age*), the level of debt (*Leverage*), and the attitude towards innovation (*R&D*) of the observed firms (all these indicators included are taken at the year before the funding to avoid simultaneity). To control for shocks common to all firms in different periods of the sample we add year fixed effects. To take account of differences in the VC markets, we also include a set of country and sector fixed effects, while we also introduce their product to control for specific characteristics of sectors across countries. All variables are defined in the text and the Appendix. The table reports coefficient estimates (resp. marginal effects) followed by robust standard errors, clustered at the deal level, in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

avoid simultaneity. Specifically, we include the log of total assets to control for size, firm age, leverage and an indicator for R&D investments. In the specifications in columns (2)-(5) different sets of fixed effects are added. In particular, year fixed effects control for common time-varying shocks that might affect the probability of raising venture capital financing.[18] Country and sector fixed effects allow us to take into account time-invariant unobservable correlated with financing that are specific to the country and to the sector where the firms operate, respectively. Lastly, in the most stringent specification, we include interacted country- and sector-specific fixed effects.[19]

We find that the coefficient for the *GreenPat* indicator is positive and highly statistically significant throughout the different models. The magnitude of the associated marginal effects is fairly stable across the specifications without controls, with the coefficients ranging between 15 and 19%. Holding a green patent increases the probability that a firm raises VC financing by around 19% when we control for the full set of fixed effects (Column (5)). Importantly, this effect is identified separately from the impact of non-green patents. The coefficient on the *OtherPat* is also positive and highly statistically significant. The associated marginal effects point to an increase in the probability of raising VC finance by 14% for firms that have already engaged in patenting activities in areas other than green technologies.

Overall, these results corroborate the view that patents act as positive signal towards VC. Moreover, importantly, we also uncover a strong effect for patents associated to green technologies, also when we control for size, age, debt capital structure, R&D and other unobservable characteristics of firms via fixed effects. Hence, green innovation seems to provide an additional signal to VC investors compared to alternative types of corporate innovation activities.

4.2. Baseline results on the matched sample

In the next step, we run the Probit model that links VC financing to patents on the matched sample of similar firms. Compared to the full sample with up to 5,775 observations, as discussed above, performing the matching reduces the sample size to 4,735. First, we consider the baseline specification with the two indicators that measure whether the firm already holds at least a green or a non-green patent at the time when VC funds are received. The results are reported in Table 4. Reassuringly, the coefficient estimates (Panel A) and associated marginal effects (Panel B) are positive, highly statistically significant, and qualitatively similar to the results obtained for the full sample[20]

The size of the marginal effects indicates that the presence of green patenting increases the probability of receiving VC finance by up to 20%, as obtained in the full specification (Column (5)). For non-green patents, the estimated impact is about 14% and varies between 12% and 14% across specifications. Therefore, the analysis of similar firms

[18]The global financial crisis and the sovereign debt crisis represent major financing shocks in the sample period. The use of year fixed effects in our model should attenuate concerns that our results are driven by these crises. Nonetheless, we have run the baseline regression on a sub-sample that excludes crisis years, i.e. from 2008 to 2012. Reassuringly, coefficient estimates and marginal effects – available upon request – are qualitatively and quantitatively similar to those obtained for the full sample period.

[19]For the sake of robustness, we also replicate the analyses shown in Table 3 substituting dummies for (green) patents and R&D investments with the natural logarithm of the number of (green) patents and R&D investments. Results presented in Table A3 of the Appendix substantially confirm the baseline findings.

[20]For the sake of robustness, as for Table 3, we also replicate the analyses shown Table 4 substituting dummies for (green) patents and R&D investments with the natural logarithm of the number of (green) patents and R&D investments. Results presented in Table A4 of the Appendix substantially confirm the baseline findings.

Table 4. Baseline model on matched sample.

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	VC = 1	VC = 1	VC = 1	VC = 1	VC = 1
Panel A – Probit Estimation					
OtherPat	0.440***	0.433***	0.409***	0.415***	0.475***
	(0.054)	(0.055)	(0.058)	(0.060)	(0.062)
GreenPat	0.602***	0.596***	0.571***	0.548***	0.684***
	(0.099)	(0.100)	(0.103)	(0.106)	(0.112)
Assets	−0.070***	−0.074***	−0.060***	−0.069***	−0.073***
	(0.012)	(0.012)	(0.013)	(0.013)	(0.014)
Age	−0.794***	−0.790***	−0.763***	−0.782***	−0.785***
	(0.032)	(0.032)	(0.034)	(0.036)	(0.038)
Leverage	−0.150**	−0.157***	−0.153**	−0.234***	−0.248***
	(0.060)	(0.060)	(0.063)	(0.068)	(0.068)
R&D	0.153	0.166	0.198	0.149	0.182
	(0.151)	(0.151)	(0.152)	(0.157)	(0.159)
Observations	4,735	4,735	4,735	4,735	4,735
Controls	Yes	Yes	Yes	Yes	Yes
Year	No	Yes	Yes	Yes	Yes
Sector	No	No	Yes	Yes	Yes
Country	No	No	No	Yes	Yes
Sector x Country	No	No	No	No	Yes
Panel B – Marginal Effects					
OtherPat	0.135***	0.131***	0.124***	0.123***	0.138***
	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)
GreenPat	0.186***	0.182***	0.174***	0.163***	0.199***
	(0.031)	(0.031)	(0.032)	(0.032)	(0.032)
Assets	−0.021***	−0.022***	−0.018***	−0.020***	−0.021***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Age	−0.237***	−0.234***	−0.226***	−0.228***	−0.225***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Leverage	−0.045**	−0.047***	−0.046**	−0.068***	−0.071***
	(0.018)	(0.018)	(0.019)	(0.020)	(0.019)
R&D	0.046	0.049	0.059	0.043	0.052
	(0.045)	(0.045)	(0.045)	(0.046)	(0.046)
Observations	4,735	4,735	4,735	4,735	4,735
Controls	Yes	Yes	Yes	Yes	Yes
Year	No	Yes	Yes	Yes	Yes
Sector	No	No	Yes	Yes	Yes
Country	No	No	No	Yes	Yes
Sector x Country	No	No	No	No	Yes

Notes: The table reports regression results, on the matched sample, of the Probit estimation of Equation 1 in Panel A and associated marginal effects in Panel B. The dependent variable is *VC*, an indicator variable that takes the value of 1 if the firm receives Venture Capital funding and 0 otherwise (i.e. receives other equity financing). *OtherPat* is an indicator variable that takes the value of 1 if the firm's patents portfolio contains non-green patents only at the year of the VC funding and 0 otherwise. *GreenPat* is an indicator variable that takes the value of 1 if the firm holds at least one green patent according to our classification at the year of VC (or other equity) funding, and 0 otherwise. The vector *Controls* includes four indicators related to the size (*Assets*), the experience (*Age*), the level of debt (*Leverage*), and the attitude towards innovation (*R&D*) of the observed firms (all these indicators included are taken at the year before the funding to avoid simultaneity). To control for shocks common to all firms in different periods of the sample we add year fixed effects. To take account of differences in the VC markets, we also include a set of country and sector fixed effects, while we also introduce their product to control for specific characteristics of sectors across countries. All variables are defined in the text and the Appendix. The table reports coefficient estimates (resp. marginal effects) followed by robust standard errors, clustered at the deal level, in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

indicates that the probability of VC raising is on average higher for firms holding at least one green patent than for firms holding non-green patents.[21]

5. Robustness tests

In this section, we verify the robustness of our baseline findings by conducting several additional tests based on different measures of green patenting activities and alternative definitions of the dependent variable, on the matched sample of similar firms.

5.1. Patent portfolio composition

To gauge the additional effect of green innovation with respect to other types of innovation activities we run an alternative specification of model (1). In particular, we replace the two indicator variables for green and non-green innovators with the (lagged) ratio between the number of green patents over the total number of patents (*GreenPatRatio*) and the total number of patents (*TotPat*) that the company holds. In this way, by focusing on their relative importance in a company's patent portfolio, we capture the contribution of green innovation activities at the extensive margin, given companies' overall level of innovation, proxied by total patents. Besides providing a measure of the intensity of green innovation, the use of this alternative variable mitigates concerns that the effect in the baseline model is driven by the correlation between the two patent indicators.

Table 5 reports the results. The coefficient of interest is positive and significant throughout Columns (1) to (4) of Panel A and turns only marginally insignificant for the full specification (Column 5).[22] The associated marginal effects in Panel B are also fairly stable across the different specifications. The magnitude of the effect is substantial, since the probability of receiving VC funds increases by between 8.8 and 11.5 % when green patents are more represented in firms' patent portfolios.

By including continuous variables among its regressors of interest (i.e. *GreenPatRatio* and *TotPat*), this model specification naturally lends itself for testing the presence of possible nonlinearities. We follow the three-step approach devised by Arin et al. (2022) that requires a graphical inspection of the relationship, a statistical analysis to identify possible switch points, and a statistical test for the presence of potential discontinuities around identified switch points. The underlying idea is that, in the presence of switch points, any discontinuity highlights nonlinearities that need to be handled with appropriate models. In Figure 1 we plot the relationship between *Prob(VC)* and *GreenPatRatio* (Panel A) or *TotPat* (Panel B), respectively, using both a locally weighted regression (left) and a Kernel-weighted local polynomial regression (right). We find that possible switch points do not emerge for *GreenPatRatio*, while are possible for *TotPat* in the surroundings of value 2.

[21]We tested the significance of the difference between the estimated coefficients and margins for *GreenPat* and *OtherPat*. Results, presented in Table A5 of the Appendix, suggest that *GreenPat* is different from *OtherPat* in a statistically significant way.

[22]However, it is likely that the inclusion of several control variables and fixed effects affects the estimator's efficiency in a more restricted sample.

Table 5. Patent portfolio composition.

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	VC = 1	VC = 1	VC = 1	VC = 1	VC = 1
Panel A – Probit Estimation					
GreenPatRatio	0.328*	0.345*	0.360*	0.335*	0.296
	(0.196)	(0.202)	(0.217)	(0.221)	(0.235)
TotPat	0.309***	0.265***	0.265***	0.207**	0.137
	(0.079)	(0.081)	(0.083)	(0.089)	(0.094)
Assets	−0.101**	−0.103**	−0.099**	−0.103**	−0.083*
	(0.042)	(0.042)	(0.045)	(0.046)	(0.048)
Age	−0.663***	−0.633***	−0.622***	−0.651***	−0.653***
	(0.102)	(0.104)	(0.111)	(0.115)	(0.121)
Leverage	−0.031	−0.080	−0.053	−0.132	−0.226
	(0.152)	(0.159)	(0.164)	(0.175)	(0.189)
R&D	−0.019	0.071	0.048	−0.071	−0.176
	(0.245)	(0.247)	(0.253)	(0.279)	(0.295)
Observations	570	570	570	570	570
Controls	Yes	Yes	Yes	Yes	Yes
Year	No	Yes	Yes	Yes	Yes
Sector	No	No	Yes	Yes	Yes
Country	No	No	No	Yes	Yes
Sector x Country	No	No	No	No	Yes
Panel B – Marginal Effects					
GreenPatRatio	0.110*	0.112*	0.115*	0.103*	0.088
	(0.066)	(0.065)	(0.069)	(0.068)	(0.070)
TotPat	0.104***	0.086***	0.085***	0.064**	0.041
	(0.026)	(0.026)	(0.026)	(0.027)	(0.028)
Assets	−0.034**	−0.033**	−0.032**	−0.032**	−0.025*
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Age	−0.222***	−0.206***	−0.199***	−0.201***	−0.194***
	(0.031)	(0.031)	(0.033)	(0.032)	(0.033)
Leverage	−0.010	−0.026	−0.017	−0.041	−0.067
	(0.051)	(0.052)	(0.053)	(0.054)	(0.056)
R&D	−0.006	0.023	0.015	−0.022	−0.052
	(0.082)	(0.080)	(0.081)	(0.086)	(0.088)
Observations	570	570	570	570	570
Controls	Yes	Yes	Yes	Yes	Yes
Year	No	Yes	Yes	Yes	Yes
Sector	No	No	Yes	Yes	Yes
Country	No	No	No	Yes	Yes
Sector x Country	No	No	No	No	Yes

Notes: The table reports regression results, on the matched sample, of the Probit estimation of Equation 1 in Panel A and associated marginal effects in Panel B. The dependent variable is *VC*, an indicator variable that takes the value of 1 if the firm receives Venture Capital funding and 0 otherwise (i.e. receives other equity financing). *GreenPatRatio*, is continuous variable that measures the ratio between the number of green over the total patents that a company holds when obtaining VC financing. *TotPat*, is a continuous variable counting the total number of (green and non-green) patents that a company holds when obtaining VC financing. The vector *Controls* includes four indicators related to the size (*Assets*), the experience (*Age*), the level of debt (*Leverage*), and the attitude towards innovation (*R&D*) of the observed firms (all these indicators included are taken at the year before the funding to avoid simultaneity). To control for shocks common to all firms in different periods of the sample we add year fixed effects. To take account of differences in the VC markets, we also include a set of country and sector fixed effects, while we also introduce their product to control for specific characteristics of sectors across countries. All variables are defined in the text and the Appendix. The table reports coefficient estimates (resp. marginal effects) followed by robust standard errors, clustered at the deal level, in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

For the second step, we then apply Hansen's test (Hansen 2000) to formally identify the switch point value for *TotPat* and check whether discontinuities emerge around it. Specifically, we replicate the estimation three times (results in Table 6): first, on the whole sample; second, including all control variables where only the coefficient of *TotPat* can vary before and after the switch point (parametric approach, estimated switch point equal

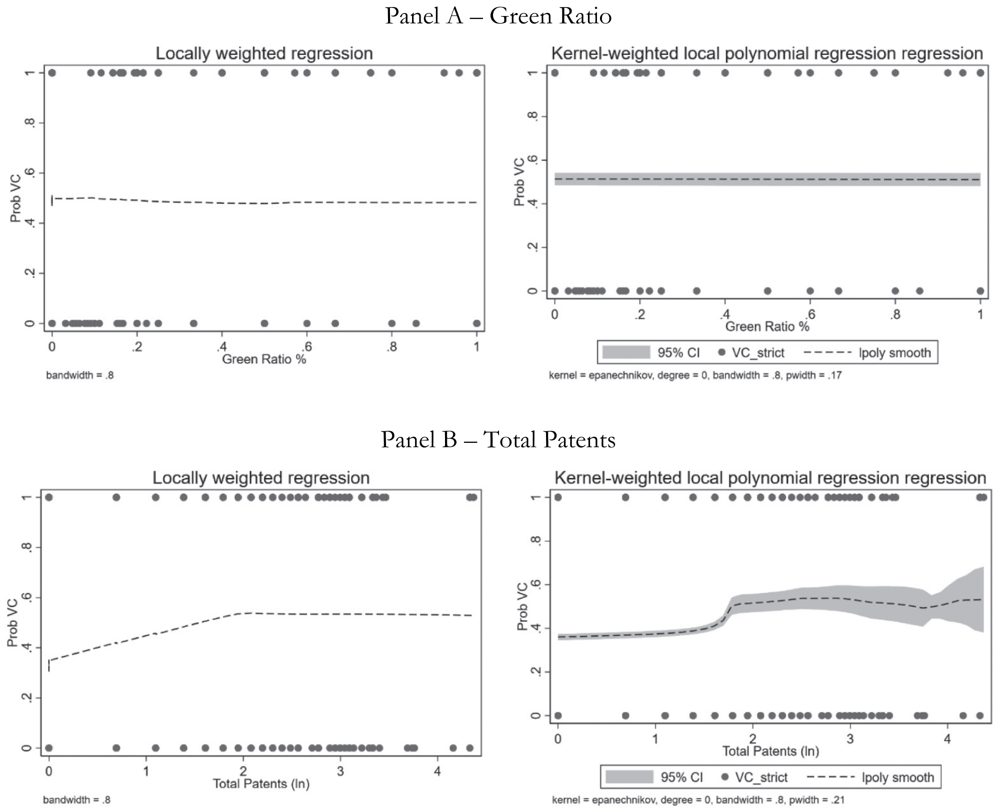

Figure 1. Test for non-linearities: preliminary graphical inspection of the data.

to 1.98 – Panel A); third, where all the regressors (control variables included) can vary before and after the switch point (non-parametric approach, estimated switch point equal to 2.08 – Panel B). Column 1 reports the results of the estimation on the whole sample, while Columns (2) and (3) include estimations limited to the sub-samples before and after the switch points, respectively. We find that the coefficients in the two sub-samples split by the switch point share the same sign and statistical significance of the estimated coefficient for the whole sample. Therefore, we conclude on the absence of relevant non-linearities in the relationship between (number of) patents and likelihood to get VC.

Lastly, we focus on the behaviour of the relationships in the surroundings of the switch point using the Kernel-weighted local polynomial regression. Table 7 shows the results of this statistical test and reports the estimate of the vertical distance between the two lines or the two polynomial approximations (order 5), respectively. Both tests do not show statistically significant discontinuities in the data close to the switch points, thus suggesting that we do not need to account for specific methods to deal with jumps in data (e.g. RDD) in our exercise. Hence, our previous results are confirmed.

Overall, in line with the results for the baseline specification, we find that firms engaging in green innovation are more likely to attract VC investments.

Table 6. Non-linearities: check on switch points.

	(1)	(2)	(3)
Dep. Variable	Coeff. whole sample	Coefficient before the switch point	Coefficient after the switch point
Panel A – Parametric estimation			
TotPat	0.207**	0.173***	0.216***
	(0.089)	(0.051)	(0.075)
Switch Point		1.95	
Panel B – Non-parametric estimation			
TotPat	0.207**	0.123**	0.209**
	(0.089)	(0.050)	(0.088)
Switch Point		2.08	

Notes: The table reports regression results, on the matched sample, of the Hansen's test (Hansen 2000) as a parametric (Panel A) and a non-parametric (Panel B) estimation. *TotPat*, is a continuous variable counting the total number of (green and non-green) patents that a company holds when obtaining VC financing. The table reports coefficient estimates followed by robust standard errors, clustered at the deal level, in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 7. Non-linearities: test to detect discontinuities around the switch points.

	(1)	(2)
Order of the polynomial function	Parametric	Non-parametric
1 (straight line)	−0.040	0.242
	(0.204)	(0.263)
5	0.240	0.914
	(0.396)	(0.689)
Switch Point	1.95	2.08

Notes: The table reports regression results, on the matched sample, of RDD estimations around the switch points for both parametric and non-parametric approaches. *Results are robust to bias-corrected and robust bias-corrected confidence intervals*. The table reports coefficient estimates followed by robust standard errors, clustered at the deal level, in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

5.2. Alternative VC definition

We now analyse whether the impact of green patenting on the firm's likelihood of receiving VC funding is driven by our definition of VC financing. Specifically, instead of using the dependent variable *VC*, we adopt a broader definition of VC investment (*VC broad*) that includes Accelerator, Business Angels, Venture Recapitalization, Venture leasing and Corporate Venture Capital in addition to the funding rounds of the variable *VC*. Then, we estimate Equation 1 with *VC broad* as a dependent variable. The results of this analysis are reported in Columns (1)-(5) of Table 8. The coefficients of *OtherPat* and *GreenPat* are both positive and statistically significant. Looking at the magnitude of coefficients, the table shows that both are in line with those shown for our stricter indicator *VC*. We conclude that the adoption of a stricter definition of VC does not overrate the probability of investing in green technologies.

5.3. Alternative measures of green innovation

In our baseline model, we have classified firms into three mutually exclusive categories: i) firms without any patents, ii) firms with at least one green patent, and iii) firms with at least one non-green patent and no green patents. One might argue that this classification does not perfectly identify green innovators and cannot precisely discriminate them from

Table 8. Alternative VC definition (VC broad).

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	$VC_{broad} = 1$	$VC_{broad} = 1$	$VC_{broad} = 1$	$VC_{broad} = 1$	$VC_{broad} = 1$
Panel A – Probit Estimation					
OtherPat	0.358***	0.358***	0.329***	0.334***	0.398***
	(0.057)	(0.057)	(0.060)	(0.062)	(0.064)
GreenPat	0.567***	0.578***	0.562***	0.545***	0.655***
	(0.105)	(0.105)	(0.109)	(0.111)	(0.117)
Assets	−0.129***	−0.131***	−0.116***	−0.123***	−0.127***
	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
Age	−0.849***	−0.845***	−0.812***	−0.821***	−0.829***
	(0.034)	(0.034)	(0.036)	(0.037)	(0.039)
Leverage	−0.217***	−0.218***	−0.223***	−0.310***	−0.329***
	(0.061)	(0.061)	(0.064)	(0.069)	(0.069)
R&D	0.153	0.150	0.192	0.169	0.209
	(0.154)	(0.156)	(0.155)	(0.160)	(0.162)
Observations	4,735	4,735	4,735	4,735	4,735
Controls	Yes	Yes	Yes	Yes	Yes
Year	No	Yes	Yes	Yes	Yes
Sector	No	No	Yes	Yes	Yes
Country	No	No	No	Yes	Yes
Sector x Country	No	No	No	No	Yes
Panel B – Marginal Effects					
GreenPatRatio	0.105***	0.104***	0.095***	0.094***	0.109***
	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)
TotPat	0.166***	0.168***	0.161***	0.153***	0.178***
	(0.030)	(0.030)	(0.031)	(0.031)	(0.030)
Assets	−0.037***	−0.038***	−0.033***	−0.035***	−0.035***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Age	−0.246***	−0.243***	−0.232***	−0.231***	−0.228***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Leverage	−0.063***	−0.063***	−0.064***	−0.087***	−0.091***
	(0.017)	(0.017)	(0.018)	(0.019)	(0.019)
R&D	0.044	0.043	0.055	0.047	0.057
	(0.045)	(0.045)	(0.044)	(0.045)	(0.044)
Observations	4,735	4,735	4,735	4,735	4,735
Controls	Yes	Yes	Yes	Yes	Yes
Year	No	Yes	Yes	Yes	Yes
Sector	No	No	Yes	Yes	Yes
Country	No	No	No	Yes	Yes
Sector x Country	No	No	No	No	Yes

Notes: The table reports regression results of the Probit estimation of Equation 1 on the matched sample (Panel A) and its marginal effects (Panel B). The dependent variable is *VC broad*, an indicator variable that takes the value of 1 if the firm receives Venture Capital funding according to our broader definition (i.e. also including Business Angel, CVC, Venture Leasing, Venture Recapitalization) and 0 otherwise (i.e. receives other equity financing). *OtherPat* is an indicator variable that takes the value of 1 if the firm's patents portfolio contains non-green patents only at the year of the VC funding and 0 otherwise. *GreenPat* is an indicator variable that takes the value of 1 if the firm holds at least one green patent according to our classification at the year of VC (or other equity) funding, and 0 otherwise. The vector *Controls* includes four indicators related to the size (*Assets*), the experience (*Age*), the level of debt (*Leverage*), and the attitude towards innovation (*R&D*) of the observed firms (all these indicators included are taken at the year before the funding to avoid simultaneity). To control for shocks common to all firms in different periods of the sample we add year fixed effects. To take account of differences in the VC markets, we also include a set of country and sector fixed effects, while we also introduce their product to control for specific characteristics of sectors across countries. All variables are defined in the text and the Appendix. The table reports coefficient estimates (resp. marginal effects) followed by robust standard errors, clustered at the deal level, in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

non-green innovators given that, in principle, the same firm might hold both green and non-green patents. This could induce potential measurement error hampering the empirical identification of the effect of green innovation. To address this concern, we run our baseline model on two restricted sub-samples of firms. In the first exercise, we exclude from the sample those firms having both types of patents with green ones being less than 50% of the total. In other words, we consider as 'green innovators' only those firms whose patent portfolio is mostly composed by green innovations (*Mostly green patents*). In the second exercise, we exclude from the sample firms having a 'mixed' patent portfolio, that is all those companies holding both green and non-green patents at the time of the financing, and we compare firms holding non-green patents only (*Fully other patents*) and green patents only (*Fully green patents*).

The results of these analyses are presented in Table 9 Columns (1) and (2), respectively. All the estimated coefficients are positive and statistically significant. The marginal effect of *Fully green patents* is lower in magnitude (0.112) with respect to the one calculated for the *Mostly green patents* coefficient (0.197), which is fully aligned with that of our baseline model. All in all, these findings confirm the robustness of our identification strategy.

Another potential issue arises with respect to the measurement of green innovation. Specifically, we classify green innovators only on the basis of the analysis of firms' patent portfolios. Hence, in our approach, we discard firms operating in innovative green sectors that, however, have not registered any green patents. While this implies that we might indeed be identifying a lower bound in the effect of green innovation on the probability of obtaining VC funding, it is nonetheless relevant to assess our results against a broader definition of green innovation. Thus, following Mrkajic, Murtinu, and Scalera (2019), we adopt an industry-based definition of green innovative firms. Specifically, we first define as 'green macro-sectors' and 'green micro-sectors' those broad and 4-digit NACE2 sectors, respectively, with at least one firm holding a green patent. Then, we tag as green all other firms in these sectors, even if they do not hold a green patent. This approach allows us to reduce the likelihood of 'false negatives' in our setting.[23]

The results of this robustness analysis are presented in Table 9, Columns (3) and (4). Column (3) shows that the probability of raising a VC is not higher for firms belonging to green macro-sectors than non-green macro-sectors, thus suggesting that the 'born-to-be-green' characteristics of firms are patent-specific and not sector-specific. However, while the magnitude of the coefficient is more than halved, the analysis at the micro-sector (4-digit) level qualitatively confirms the results obtained in our baseline estimation. This suggests that a higher granularity in the identification of green innovations helps in the specification of the model, and, more importantly, in drawing the correct inference about its relevance for attracting VC investments.

Another possible concern related to the correct identification of the model is linked to the fact that not all companies might have the financial resources to register and hold a patent especially in Europe (van Pottelsberghe de la Potterie and François 2009) despite being innovative. This possibility could be particularly common among start-ups which more typically suffer from financial constrains

[23]A similar methodology is adopted by Bellucci et al. (2023) to test the robustness of the results of a model in which the identification strategy was based on a deal-level analysis rather than an industry-level analysis.

Table 9. Robustness: mostly green, only green patents, sectoral analyses and R&D.

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	VC = 1	VC = 1	VC = 1	VC = 1	VC = 1
Panel A – Probit Estimation					
Fully other patents	0.490***	0.492***			
	(0.063)	(0.063)			
Mostly green patents	0.681***				
	(0.171)				
Fully green patents		0.388*			
		(0.231)			
Green Macro Sectors			0.404		
			(1.113)		
Green Micro Sectors				0.195***	
				(0.051)	
OtherPat					0.449***
					(0.055)
GreenPat					0.574***
					(0.102)
Assets	−0.076***	−0.078***	−0.068***	−0.065***	−0.070***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.012)
Age	−0.791***	−0.787***	−0.754***	−0.752***	−0.797***
	(0.039)	(0.039)	(0.037)	(0.037)	(0.032)
Leverage	−0.223***	−0.234***	−0.236***	−0.226***	−0.153**
	(0.068)	(0.069)	(0.068)	(0.068)	(0.061)
R&D	0.147	0.111	0.262	0.231	
	(0.165)	(0.175)	(0.161)	(0.162)	
Observations	4,113	4,081	4,241	4,241	4,618
Controls	Yes	Yes	Yes	Yes	Yes (no R&D)
Year	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes
Sector x Country	Yes	Yes	Yes	Yes	Yes
Panel B – Marginal Effects					
Fully other patents	0.142***	0.142***			
	(0.018)	(0.018)			
Mostly green patents	0.197***				
	(0.049)				
Fully green patents		0.112*			
		(0.067)			
Green Macro Sectors			0.118		
			(0.326)		
Green Micro Sectors				0.057***	
				(0.015)	
OtherPat					0.137***
					(0.017)
GreenPat					0.176***
					(0.032)
Assets	−0.022***	−0.022***	−0.020***	−0.019***	−0.021***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age	−0.0226***	−0.224***	−0.220***	−0.219***	−0.238***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
Leverage	−0.063***	−0.067***	−0.069***	−0.066***	−0.046**
	(0.019)	(0.020)	(0.020)	(0.020)	(0.018)
R&D	0.042	0.032	0.077	0.067	
	(0.047)	(0.050)	(0.047)	(0.047)	
Observations	4,113	4,081	4,241	4,241	4,618
Controls	Yes	Yes	Yes	Yes	Yes (no R&D)
Year	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes
Sector x Country	Yes	Yes	Yes	Yes	Yes

(Baños-Caballero and García-Teruel 2023; Huyghebaert 2006; Huyghebaert, Van de Gucht, and Van Hulle 2007; Moraes Silva, Lucas, and Vonortas 2020). These companies could adopt different signals to try to attract external equity financing, such as R&D expenditure (Baum and Silverman 2004). Hence, the presence of companies showing R&D expenditure among those that do not hold any patent could affect the counterfactual of our analysis, potentially leading to a bias in the findings. While previous studies suggest a strong and significant correlation between firms' R&D efforts and presence of patents (Caviggioli et al. 2020; Lahr and Mina 2016), we conduct a robustness test aimed at reducing this potential bias by estimating Equation 1 in the sub-sample of companies that do not show any R&D expenditure. In this way, we limit the analysis by investigating whether companies without R&D expenditure are more prone to raise a VC with respect to other equity financing in case they hold patents. The results of this robustness analysis are shown in Table 9, column (5), and show that – even excluding from the analysis companies that may have used other innovation signals to attract private investors (i.e. R&D expenditure) other than patents – firms with green patents are more likely to be financed by VC vs. other forms of equity-financing than those holding non-green patents, thus further confirming our main results.

Overall, these analyses confirm the main messages from our baseline findings, that is, that green patenting is an important driver of VC funding. Moreover, the merits of granular data at the firm level on innovation activities are apparent in the fact that, when using macro indicators at the sector level, one would erroneously conclude that there is no association between green innovation and VC finance. This indeed suggests that VC finance can play an important role in fostering green innovation.

Notes: The table reports regression results, on the matched sample, of the Probit estimation of Equation 1 in Panel A and associated marginal effects in Panel B. The dependent variable is *VC*, an indicator variable that takes the value of 1 if the firm receives Venture Capital funding and 0 otherwise (i.e. receives other equity financing). In column (1) we exclude from the sample firms having a 'mixed' patent portfolio, that is all those companies holding both green and non-green patents at the time of the financing, and we compare firms holding non-green patents only (*Fully other patents*) and green patents only (*Fully green patents*). *Fully other patents* is an indicator variable that takes the value of 1 if the firm holds at least one patent at the year of VC (or other equity) funding, and 0 otherwise. In column (2) we exclude from the sample firms having less than 50% of green patents in their patent portfolio. *Mostly green patents* is an indicator variable that takes the value of 1 if the firm's patent portfolio is composed by more than 50 % of green patents. In column (3), the variable *Green Macro Sectors* is an indicator variable that takes the values of 1 if a firm operates in a 'green macro-sectors', represented by those NACE2 'broad 'sectors with at least one firm holding any green patent. In column (4), *Green Micro Sectors* is an indicator variable that take the values of 1 if a firm operates in a 'green micro-sectors', represented by those 4-digit sectors with at least one firm holding any green patent. In column (5), *OtherPat* is an indicator variable that takes the value of 1 if the firm's patents portfolio contains non-green patents only at the year of the VC funding and 0 otherwise. *GreenPat* is an indicator variable that takes the value of 1 if the firm holds at least one green patent according to our classification at the year of VC (or other equity) funding, and 0 otherwise. The vector *Controls* includes four indicators related to the size (*Assets*), the experience (*Age*), the level of debt (*Leverage*), and the attitude towards innovation (*R&D*) of the observed firms (all these indicators included are taken at the year before the funding to avoid simultaneity). *R&D* is not included in the estimations related to column (5). To control for shocks common to all firms in different periods of the sample we add year fixed effects. To take account of differences in the VC markets, we also include a set of country and sector fixed effects, while we also introduce their product to control for specific characteristics of sectors across countries. All variables are defined in the text and the Appendix. The table reports coefficient estimates (resp. marginal effects) followed by robust standard errors, clustered at the deal level, in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 10. Heterogeneous effects on green patenting.

Dep. Variable	(1) VC Later = 1	(2) VC = 1	(3) CVC = 1	(4) BA = 1
	VC Early = 0	Multiple Deal = No	VC = 0	VC = 0
Panel A – Probit Estimation				
OtherPat	−0.076	0.481***	−0.198	−0.559***
	(0.113)	(0.063)	(0.164)	(0.187)
GreenPat	−0.073	0.722***	−0.151	−1.128**
	(0.198)	(0.112)	(0.319)	(0.477)
Assets	0.304***	−0.068***	0.088**	−0.222***
	(0.034)	(0.014)	(0.043)	(0.037)
Age	1.019***	−0.802***	0.328**	0.187
	(0.101)	(0.038)	(0.147)	(0.117)
Leverage	0.182	−0.239***	0.091	−0.190
	(0.126)	(0.068)	(0.200)	(0.151)
R&D	0.488	0.209	0.231	
	(0.311)	(0.162)	(0.521)	
Observations	1,549	4,175	1,387	1,513
Controls	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Sector x Country	Yes	Yes	Yes	Yes
Panel B – Marginal Effects				
OtherPat	−0.017	0.139***	−0.015	−0.052***
	(0.025)	(0.018)	(0.012)	(0.013)
GreenPat	−0.016	0.208***	−0.012	−0.075***
	(0.043)	(0.031)	(0.023)	(0.012)
Assets	0.067***	−0.019***	0.007**	−0.026***
	(0.007)	(0.004)	(0.004)	(0.005)
Age	0.226***	−0.230***	0.028**	0.022
	(0.020)	(0.009)	(0.013)	(0.014)
Leverage	0.040	−0.068***	0.008	−0.022
	(0.028)	(0.019)	(0.017)	(0.018)
R&D	0.108	0.060	0.019	-
	(0.069)	(0.046)	(0.044)	
Observations	1,549	4,175	1,387	1,513
Year	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Sector x Country	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: The table reports regression results, on the matched sample, of the Probit estimation of Equation 1 in Panel A and associated marginal effects in Panel B. In column (1), we analyse the possible differential effect for early and late VC investments, we construct a dummy variable, *Later Stage*, which takes the value of 1 for later-stage deals (all stages from the 3rd to 9th rounds and VC later), and 0 for early-stage ones. In column (2), we focus our analyses on the subset of firms that in the period of analyses have raised only one VC investment. In column (3), we analyse possible heterogeneous effects created by different types of investors. Specifically, we distinguish between Independent Venture Capital investors (IVC) and Venture Capital investments made by Corporations (CVC). The dependent variable, *CVC*, is an indicator that takes the value of 1 for deals involving a corporate VC, and 0 for independent VC. In column (4), we distinguish between investments made by Business Angels (BAs) and IVCs when investing in the presence of (green) patents. In this exercise, we limit our sample to firms that raised BA and IVC investments. The dependent variable, *BA*, is an indicator that takes the value of 1 for deals involving a Business Angels (BAs), and 0 for IVC. The vector *Controls* includes four indicators related to the size (*Assets*), the experience (*Age*), the level of debt (*Leverage*), and the attitude towards innovation (*R&D*) of the observed firms (all these indicators included are taken at the year before the funding to avoid simultaneity). To control for shocks common to all firms in different periods of the sample we add year fixed effects. To take account of differences in the VC markets, we also include a set of country and sector fixed effects, while we also introduce their product to control for specific characteristics of sectors across countries. All variables are defined in the text and the Appendix. The table reports coefficient estimates (resp. marginal effects) followed by robust standard errors, clustered at the deal level, in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

6. Heterogeneous effects

To investigate whether there is evidence of heterogeneous effects, we analyse how the probability of receiving VC funding is driven by the investment stage of financing, by investor characteristics and by the geographical dimension.

6.1. Investment stage

While patenting can be thought as a relevant signal for VC investors to reduce information asymmetries in the first stages of investments, this aspect could be less relevant when the relationship between investor and VC-backed firm is more consolidated, that is for the later rounds of investments. However, existing evidence on the relationship between patents and VC seems to be mixed, with some studies suggesting that VCs are less interested in companies' patenting activities when they are deciding whether to fund a later stage investment (Hoenen et al. 2014; Zhou et al., 2016), and others finding that patents play a more relevant signalling role at least after the first VC deal (Mann and Sager, 2007) and that patents are relevant VC signals in later stages also in combination with other earlier financial signals (e.g. crowdfunding) (Roma, Vasi, and Kolympiris 2021). At the same time, this latter hypothesis could be furtherly confirmed in the case of green patents due to the longer average time needed to develop patentable green technologies (Mrkajic, Murtinu, and Scalera 2019). Hence, we further investigate possible heterogeneous effects related to the stage of financing by distinguishing between early and late investment rounds. In particular, we compare the probability of raising a Later- vs Early-stage VC in the presence of (green) patents.

To analyse the possible differential effect for early and late investments, we construct a dummy variable, *Later Stage*, which takes the value of 1 for later-stage deals, and 0 for early-stage ones. We consider seed stage, as well as the 1st and 2nd investment rounds as early-stage. By contrast, we categorise as later stage all stages from the 3rd to 9th rounds and VC later. We then estimate Equation 1 with the variable *Later Stage* as a dependent variable. Were the estimated coefficient significantly negative, we could conclude that later-stage VC investments are less influenced by the presence of (green) patenting than early-stage ones.

The results of the estimation are shown in Column (1) of Table 10. The coefficients of the variable *GreenPat* and *OtherPat* are both negative (as expected) but not statistically significant, which means that we do not find any significant differences across VC investment rounds.

For the sake of robustness and in order to more directly isolate the signalling effect of (green) patents on VC, we perform another estimation replicating Equation 1 on the sub-sample of firms that received only one VC or other equity-financing in the period of interest. This analysis should also minimise possible serial correlation bias due to interactions among investments performed by VC investors. The results of this analysis are shown in Column (2) of Table 10. Reassuringly, they confirm baseline results, showing positive and significant coefficients and margins for both green and non-green patents with larger magnitudes emerging in the case of green patents. This finding, together with the previous shown in Column (1), further confirms the presence of (green) patents is equally important for receiving both stages of VC financing.

6.2. Type of investor

We also analyse possible heterogeneous effects created by different types of investors. Specifically, we distinguish between Independent Venture Capital investors (IVC) and Venture Capital investments made by Corporations (CVC). The differences between IVCs and CVCs in their organisation, incentives, objectives and mode of operation may induce different responses by these types of investors to green innovation, and different propensity to invest therein. On one hand, IVCs aim at increasing the value of portfolio companies prior to exit (Gompers and Lerner, 2001). The VC funding or the acquisition of equity stakes of firms with green innovation activities and patents may increase the performance and consequently the value of these companies before exit strategy. Hence, IVCs might have the incentive to invest heavily with respect to other types of investors. On the other hand, CVCs are more likely to finance companies that develop technologies complementary to those of the parent (Da Rin, Hellmann, and Puri 2013; Dushnitsky and Lenox 2006; Maula, Keil, and Zahra 2013). In such a case, CVCs may postpone their investments waiting for more emerging and disruptive technologies. To examine the different behaviours between IVCs and CVCs towards the VC financing of green patented innovation, we create a dummy variable, *CVC*, that takes the value of 1 for deals involving a corporate VC, and 0 for independent VC. We then estimate Equation 1 with *CVC* as a dependent variable.

The estimation results are in Column (3) of Table 10. The analysis suggests that CVCs do not respond in a systematically different manner respect to IVCs, as indicated by the insignificant estimates of coefficients for green and non-green patents. According with the survey evidence reported by Gompers et al. (2020), we conclude that while relevant, the investor type is not a primary determinant for investing in green technologies in the VC market.

In another exercise, we explore the possible heterogeneous effects by distinguishing between investments made by Business Angels (BAs) and IVCs when investing in the presence of (green) patents. BAs are considered 'informal' venture capital investors (Haines, Madill, and Riding 2003) that are more interested to personal signals related to the company founders or management such as their commitment, trust and enthusiasm, while IVCs mostly base their investments on more structured and objective evaluation processes (DeGennaro 2010; Van Osnabrugge and Robinson 2000). Along this line, the fact that the company is a patent holder should attract more interest from the IVCs than from the BAs. If this is empirically validated, we also want to verify whether this different approach applies both to green and to all the other patents. Indeed, a survey by European Investment Fund (EIF) shows that although both IVCs and BAs tend to be interested in ESG investments, Angel investors are more attentive to ethical issues and impact financing (Botsari and Lang 2020). We then analyse whether the presence of (green) patents could be more likely associated to VC rather than to Angel investment. To do so, we limit our sample to firms that raised BA ($BA = 1$) and to those that received VC ($VC = 0$).

The results of this analysis are reported in Column (4) of Table 10. We find that the probability of investing in firms with green patents is lower for BAs respect to IVCs. The lower probability of BAs emerges also when they invest in firms with other non-green patents. Our results are consistent with those of Conti, Thursby, and Rothaermel (2013) who find that patenting is a more effective signal for IVCs than for BAs. At the same time, the presence of green patents does not seem to be a sufficiently strong signal for BAs to place themselves as recognised operators in the impact financing arena.

6.3. Geographical dimension

Exploring the geographical dimension of our sample allows us to test whether our main findings are sensitive to country-specific characteristics that might affect the relationship between green innovation and VC financing. The level of maturity and fund availability of venture capitalists and startup ecosystems varies significantly across European countries (Bellucci, Gucciardi, and Nepelski 2021). Significant cross-country heterogeneity also exists with respect to the laws and regulations surrounding patenting and Venture Capital (e.g. Bradley et al. 2021; Moore et al. 2015), for instance in terms of more or less prescriptive the regulations for patents (Hou, Png, and Xiong 2022), and more or less favourable tax provisions and incentives for venture capital investments (e.g. Murtinu 2021).

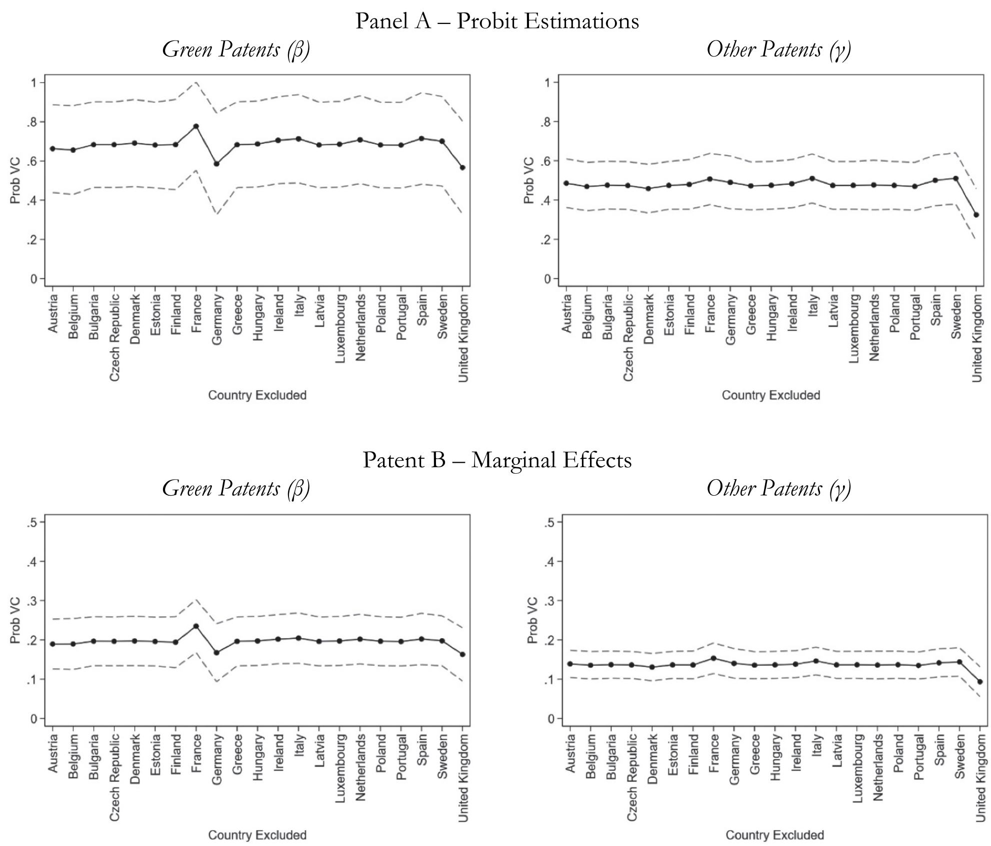

Figure 2. Geographical heterogeneity. **Notes**: The figures are obtained through the estimations of the baseline equation on the matched sample. For this reason, the number of countries is reduced to 21.

To disentangle the potential effect of such heterogeneity on the average effect from our baseline model, we estimate Equation 1 on the matched sample by dropping one country at a time.[24] By doing so, we can detect whether the behaviour of specific countries is significantly different from the European average. Figure 2 shows the result of the estimated coefficients (Panel A), β (for green patents) and γ (for other patents), related margins (Panel B), and their 95% confidence interval. Results are very similar to those obtained in our baseline specification: the estimated coefficients and margins for (green) patents are always positive and significant, and β is always larger than γ, when we exclude single countries one by one. Moreover, also the magnitude of estimated coefficients and margins are rather stable around the baseline average. There are three exceptions: the cases where we exclude Germany and the UK, where the decrease in the average coefficient suggests a high relevance of (green) patenting for VC investment with respect to other equity financing; and France, where the result is reversed. Nevertheless, also for these three cases green patents are associated to a higher probability of raising a VC with respect to other equity financing than other non-green patents. Overall, we conclude that the relationship between green patenting and VC finance holds across all countries in our sample. Country specificities do seem to matter in this area and should be addressed when investigating similar research questions.

7. Conclusions

In this paper we investigate whether, among equity-backed firms, those that have obtained green patents are more likely to attract VC financing than firms without a patented record of green innovation. We use a unique matched sample of equity-backed companies, equity transactions and information on innovation activities and patents in clean energy technologies associated to VC-backed firms over the period 2008–2017. We find that engaging in green patenting activities increases the likelihood that a firm receives VC funding compared to other forms of equity finance. The same result holds when we consider the share of green over total patents instead of an indicator that captures only the status as patented green innovator. Robustness and heterogeneous analyses corroborate the view that, in addition to general innovation activities, green patenting is an important driver of VC funding.

Overall, our findings point to green innovation as an investment opportunity for venture capitalists. This has important implications at a juncture where substantial technological innovation is crucial to meet the ambitious climate and environmental goals set at regional and global levels, and the required financial effort is equally unprecedented. In this respect, it is widely recognised that public sources of finance are largely insufficient to fund the massive amount of investment needed to move towards less environment- and resource-intensive economies and societies. For instance, in addition to public support, the initiatives pioneered by the European Commission in the area of sustainable finance indeed aim at providing a guide to private investments towards green recovery. By documenting the attractiveness of green patenting for VC investment, our findings also suggest that this type of equity finance can play an important role in fostering green innovation. This, in turn, can generate positive

[24]Specifically, we look at the country of the VC/equity -backed companies to exclude from the estimation sample countries one by one.

externalities in the form of knowledge spillovers, and thus facilitate the adoption and diffusion of environmental technologies, and, ultimately, bolster green growth.

Confirming the pivotal role of VC finance in enabling and scaling the solutions needed for the low-carbon transition calls for further analysis, in order to fully disentangle the complexity of venture funding of green technologies. Many of those solutions indeed require high level of investments over a long period and have shown to be a poor fit for the business model of traditional European VC funds (World Economic Forum 2020). A paradigmatic example are deep-tech start-ups, which build on scientific knowledge and are characterised by long R&D cycles and untested business models. They typically rely on large capex investments in pilot plants for new technologies to be able to scale their revenues.

In this context, the investigation of the interplay between public support measures and private finance is particularly relevant (Bellucci, Gucciardi, and Nepelski 2023). A favourable policy stance towards environmental issues may significantly reduce the uncertainty and risk associated to investment in green ventures (Bürer and Wüstenhagen 2009; Corrocher and Solito 2017; Mazzucato and Semieniuk 2018), particularly if it has a long-term perspective, such as policies that are aimed at creating a market for environmental technologies (Criscuolo and Menon 2015). This suggests that, within the broader the policy efforts to reduce the equity financing gap in Europe (Gucciardi 2022), the net-zero transition plans and the environmental initiatives pioneered in the European Green Deal might indeed create favourable conditions to VC investment in green ventures. Many countries are developing support measure to incentivise and de-risk investment in green technologies, including for instance tax credits, funds and grants, as well as equity and debt co-investment. We leave this and related issues for further research.

CRediT author statement

Andrea Bellucci: Conceptualization, Methodology, Formal Analysis, Writing – Original draft, Writing – Review. **Serena Fatica**: Conceptualization, Resources, Writing – Original draft, Writing – Review. **Aliki Georgakaki**: Resources, Writing – Review. **Gianluca Gucciardi**: Conceptualization, Data curation, Methodology, Formal Analysis, Writing – Original draft, Writing – Review. **Simon Letout**: Data curation, Writing – Review, Resources. **Francesco Pasimeni**: Data curation, Resources, Writing – Original draft

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ORCID

Andrea Bellucci http://orcid.org/0000-0001-5086-6679
Serena Fatica http://orcid.org/0000-0002-9990-4354
Aliki Georgakaki http://orcid.org/0000-0002-3970-5652
Gianluca Gucciardi http://orcid.org/0000-0002-8814-5575

References

Akcigit, U., E. Dinlersoz, J. Greenwood, and V. Penciakova. 2019. Synergizing Ventures. NBER Working Paper 26196, National Bureau of Economic Research.

Amore, M. D., and M. Bennedsen. 2016. "Corporate Governance and Green Innovation." *Journal of Environmental Economics & Management* 75:54–72. https://doi.org/10.1016/j.jeem.2015.11.003.

Arin, P., M. Minniti, S. Murtinu, and N. Spagnolo. 2022. "Inflection Points, Kinks, and Jumps: A Statistical Approach to Detecting Nonlinearities." *Organizational Research Methods* 25 (4): 786–814. https://doi.org/10.1177/10944281211058466 .

Arvanitis, S., and T. Stucki. 2014. "The Impact of Venture Capital on the Persistence of Innovation Activities of Start-Ups." *Small Business Economics* 42 (4): 849–870. https://doi.org/10.1007/s11187-013-9499-3 .

Baños-Caballero, S., and P. J. García-Teruel. 2023. "Investment in Trade Credit in Small Business Start-Ups: Evidence from Spain During a Financial Crisis." *Applied Economics* 55 (3): 273–282. https://doi.org/10.1080/00036846.2022.2086685.

Baum, J. A., and B. S. Silverman. 2004. "Picking Winners or Building Them? Alliance, Intellectual, and Human Capital as Selection Criteria in Venture Financing and Performance of Biotechnology Startups." *Journal of Business Venturing* 19 (3): 411–436. https://doi.org/10.1016/S0883-9026(03)00038-7.

Bellucci, A., A. Borisov, G. Gucciardi, and A. Zazzaro. 2023. "The Reallocation Effects of COVID-19: Evidence from Venture Capital Investments Around the World." *Journal of Banking and Finance* 147:106443. https://doi.org/10.1016/j.jbankfin.2022.106443.

Bellucci, A., G. Gucciardi, and D. Nepelski. 2021. *Venture Capital in Europe. Evidence-Based Insights About Venture Capitalists and Venture Capital-Backed Firms, EUR 30480*. Luxembourg: EN, Publications Office of the European Union. https://doi.org/10.2760/076298.

Bellucci, A., G. Gucciardi, and D. Nepelski. 2023. *The Determinants of Public Grants and Venture Capital Financing: Evidence from Europe, EUR 31398*. Luxembourg: EN, Publications Office of the European Union. https://doi.org/10.2760/920754.

Bernstein, S., X. Giroud, and R. R. Townsend. 2016. "The Impact of Venture Capital Monitoring." *The Journal of Finance* 64 (4): 1591–1622. https://doi.org/10.1111/jofi.12370.

Bertoni, F., M. G. Colombo, and A. Quas. 2015. "The Patterns of Venture Capital Investment in Europe." *Small Business Economics* 45:543–560. https://doi.org/10.1007/s11187-015-9662-0 .

Bertoni, F., M. A. Ferrer, and J. Martí. 2013. "The Different Roles Played by Venture Capital and Private Equity Investors on the Investment Activity of Their Portfolio Firms." *Small Business Economics* 40:607–633. https://doi.org/10.1007/s11187-011-9384-x.

Block, J., C. Fisch, S. Vismara, and R. Andres. 2019. "Private Equity Investment Criteria: An Experimental Conjoint Analysis of Venture Capital, Business Angels, and Family Offices." *Journal of Corporate Finance* 58:329–352. https://doi.org/10.1016/j.jcorpfin.2019.05.009.

Botsari, A., and F. Lang. 2020. ESG Considerations in Venture Capital and Business Angel Investment Decisions: Evidence from Two Pan-European Surveys (No. 2020/63). EIF Working Paper.

Bradley, S. W., P. H. Kim, P. G. Klein, J. S. McMullen, and K. Wennberg. 2021. "Policy for Innovative Entrepreneurship: Institutions, Interventions, and Societal Challenges." *Strategic Entrepreneurship Journal* 15 (2): 167–184. https://doi.org/10.1002/sej.1395.

Breuer, W., and A. Pinkwart. 2018. "Venture Capital and Private Equity Finance as Key Determinants of Economic Development." *Journal of Business Economics* 88:319–324. https://doi.org/10.1007/s11573-018-0892-x.

Bürer, M. J., and R. Wüstenhagen. 2009. "Which Renewable Energy Policy is a Venture Capitalist's Best Friend? Empirical Evidence from a Survey of International Cleantech Investors." *Energy Policy* 37 (12): 4997–5006. https://doi.org/10.1016/j.enpol.2009.06.071.

Cao, J., and P. H. Hsu. 2011. The Informational Role of Patents in Venture Capital Financing. *Available at SSRN 1678809*.

Carpenter, R. E., and B. C. Petersen. 2002. "Capital Market Imperfections, High-Tech Investment, and New Equity Financing." *The Economic Journal* 112 (477): F54–F72.

Caviggioli, F., A. Colombelli, A. De Marco, and E. Paolucci. 2020. “How Venture Capitalists Evaluate Young Innovative Company Patent Portfolios: Empirical Evidence from Europe.” *International Journal of Entrepreneurial Behavior & Research* 26 (4): 695–721. https://doi.org/10.1108/IJEBR-10-2018-0692.

Conti, A., M. Thursby, and F. T. Rothaermel. 2013. “Show Me the Right Stuff: Signals for High-Tech Startups.” *Journal of Economics & Management Strategy* 22 (2): 341–364. https://doi.org/10.1111/jems.12012.

Corrocher, N., and I. Solito. 2017. “How Do Firms Capture Value from Environmental Innovations? An Empirical Analysis on European SMEs.” *Industry & Innovation* 24 (5): 569–585. https://doi.org/10.1080/13662716.2017.1302792.

Criscuolo, C., and C. Menon. 2015. “Environmental Policies and Risk Finance in the Green Sector: Cross-Country Evidence.” *Energy Policy* 83:38–56. https://doi.org/10.1016/j.enpol.2015.03.023.

Cumming, D. J., and S. Vismara. 2017. “De-Segmenting Research in Entrepreneurial Finance.” *Venture Capital* 19 (1–2): 17–27. https://doi.org/10.1080/13691066.2016.1225910.

Da Rin, M., T. Hellmann, and M. Puri. 2013. “A Survey of Venture Capital Research.” In *Handbook of the Economics of Finance*, 573–648. Vol. 2. Elsevier. https://doi.org/10.1016/B978-0-44-453594-8.00008-2 .

Da Rin, M., and M. F. Penas The Effect of Venture Capital on Innovation Strategies. 2007. *NBER Working Paper No. w13636*.

DeGennaro, R. P. 2010. “Angel Investors: Who They are and What They Do; Can I Be One, Too?” *Journal of Wealth Management* 13 (2): 55–60. https://doi.org/10.3905/jwm.2010.13.2.055.

Demirel, P., Q. C. Li, F. Rentocchini, and J. P. Tamvada. 2019. “Born to Be Green: New Insights into the Economics and Management of Green Entrepreneurship.” *Small Business Economics* 52 (4): 759–771. https://doi.org/10.1007/s11187-017-9933-z .

De Vries, G., E. Pennings, J. H. Block, and C. Fisch. 2017. “Trademark or Patent? The Effects of Market Concentration, Customer Type and Venture Capital Financing on Start-ups’ Initial IP Applications.” *Industry & Innovation* 24 (4): 325–345. https://doi.org/10.1080/13662716.2016.1231607.

Diodato, D., P. Moncada-Paternò-Castello, F. Rentocchini, and A. Tübke. 2022. “*Industrial innovation for sustainable competitiveness: Science-for-policy insights.*“ JRC128430. Seville (Spain): European Commission, Joint Research Centre – Directorate for Growth and Innovation.

Dong, W., Y. Li, X. Lv, and C. Yu. 2021. “How Does Venture Capital Spur the Innovation of Environmentally Friendly Firms? Evidence from China.” *Energy Economics* 103:105582. https://doi.org/10.1016/j.eneco.2021.105582 .

Drover, W., L. Busenitz, S. Matusik, D. Townsend, A. Anglin, and G. Dushnitsky. 2017. “A Review and Road Map of Entrepreneurial Equity Financing Research: Venture Capital, Corporate Venture Capital, Angel Investment, Crowdfunding, and Accelerators.” *Journal of Management* 43 (6): 1820–1853. https://doi.org/10.1177/0149206317690584.

Dushnitsky, G., and M. J. Lenox. 2006. “When Does Corporate Venture Capital Investment Create Firm Value?” *Journal of Business Venturing* 21 (6): 753–772. https://doi.org/10.1016/j.jbusvent.2005.04.012.

Engel, D., and M. Keilbach. 2007. “Firm-Level Implications of Early Stage Venture Capital Investment—An Empirical Investigation.” *Journal of Empirical Finance* 14 (2): 150–167. https://doi.org/10.1016/j.jempfin.2006.03.004.

Faria, A. P., and N. Barbosa. 2014. “Does Venture Capital Really Foster Innovation?” *Economics Letters* 122 (2): 129–131. https://doi.org/10.1016/j.econlet.2013.11.014.

Farre-Mensa, J., D. Hegde, and A. Ljungqvist. 2020. “What is a Patent Worth? Evidence from the US Patent “Lottery”.” *The Journal of Finance* 75 (2): 639–682. https://doi.org/10.1111/jofi.12867.

Fiorini, A., A. Georgakaki, F. Pasimeni, and E. Tzimas. 2017. “Monitoring R&I in Low-Carbon Energy Technologies.” In *EUR 28446 EN*. Luxembourg: Publications Office of the European Union. https://doi.org/10.2760/434051.

Florida, R. L., and M. Kenney. 1988. “Venture Capital-Financed Innovation and Technological Change in the USA.” *Research Policy* 17 (3): 119–137. https://doi.org/10.1016/0048-7333(88)90038-8.

Gaddy, B., V. Sivaram, T. Jones, and L. Wayman. 2017. "Venture Capital and Cleantech: The Wrong Model for Energy Innovation." *Energy Policy* 102 (1): 385–395. https://doi.org/10.1016/j.enpol.2016.12.035 .

Ghosh, S., and R. Nanda. 2010. Venture Capital Investment in the Clean Energy Sector. Harvard Business School Working Paper, 11–020.

Gompers, P. A., W. Gornall, S. N. Kaplan, and I. A. Strebulaev. 2020. "How Do Venture Capitalists Make Decisions?" *Journal of Financial Economics* 135 (1): 169–190. https://doi.org/10.1016/j.jfineco.2019.06.011 .

Gompers, P., W. Gornall, S. N. Kaplan, and I. A. Strebulaev. 2021. "Venture Capitalists and COVID-19." *The Journal of Financial and Quantitative Analysis* 56 (7): 2474–2499. https://doi.org/10.1017/S0022109021000545 .

Gompers, P., and J. Lerner. 2001. "The venture capital revolution." *Journal of Economic Perspectives* 15 (2): 145–168.

Gompers, P., and J. Lerner. 2004. *The Venture Capital Cycle*. Cambridge: MIT Press.

Gucciardi, G. 2022. "Measuring the Relative Development and Integration of EU countries' Capital Markets Using Composite Indicators and Cluster Analysis." *Review of World Economics* 158 (4): 1043–1083. https://doi.org/10.1007/s10290-022-00453-6.

Haeussler, C., D. Harhoff, and E. Mueller. 2014. "How Patenting Informs VC Investors–The Case of Biotechnology." *Research Policy* 43 (8): 1286–1298. https://doi.org/10.1016/j.respol.2014.03.012.

Haines, G. H., Jr, J. J. Madill, and A. L. Riding. 2003. "Informal Investment in Canada: Financing Small Business Growth." *Journal of Small Business & Entrepreneurship* 16 (3–4): 13–40. https://doi.org/10.1080/08276331.2003.10593306.

Hall, B. H. 2002. "The Financing of Research and Development." *Oxford Review of Economic Policy* 18 (1): 35–51. https://doi.org/10.1093/oxrep/18.1.35.

Hall, B. H. 2019. "Is There a Role for Patents in the Financing of New Innovative Firms?" *Industrial and Corporate Change* 28 3 1–24.

Hall, B. H., and J. Lerner. 2010. "The Financing of R&D and Innovation." In *Handbook of the Economics of Innovation*, 609–639. Vol. 1. North-Holland. https://doi.org/10.1016/S0169-7218(10)01014-2.

Hansen, B. E. 2000. "Sample Splitting and Threshold Estimation." *Econometrica* 68 (3): 575–603. https://doi.org/10.1111/1468-0262.00124.

Heger, D., and K. Hussinger. 2017. "Implications of Uncertain Patent Rights for German Start-ups' Commercialisation Activities and Access to External Capital." *Industry & Innovation* 24 (7): 753–773. https://doi.org/10.1080/13662716.2016.1264066.

Hirukawa, M., and M. Ueda. 2011. "Venture Capital and Innovation: Which is First?" *Pacific Economic Review* 16 (4): 421–465. https://doi.org/10.1111/j.1468-0106.2011.00557.x.

Hoenen, S., C. Kolympiris, W. Schoenmakers, and N. Kalaitzandonakes. 2014. "The Diminishing Signaling Value of Patents Between Early Rounds of Venture Capital Financing." *Research Policy* 43 (6): 956–989. https://doi.org/10.1016/j.respol.2014.01.006.

Hoenig, D., and J. Henkel. 2015. "Quality Signals? The Role of Patents, Alliances, and Team Experience in Venture Capital Financing." *Research Policy* 44:1049–1064. https://doi.org/10.1016/j.respol.2014.11.011.

Hottenrott, H., B. H. Hall, and D. Czarnitzki. 2017. "Patents as Quality Signals? The Implications for Financing Constraints on R&D." *Economics of Innovation & New Technology* 25 (3): 197–217. https://doi.org/10.1080/10438599.2015.1076200.

Hou, Y., I. P. L. Png, and X. Xiong. 2022. "When Stronger Patent Law Reduces Patenting: Empirical Evidence." *Strategic Management Journal* 44 (4): 977–1012. https://doi.org/10.1002/smj.3464 .

Howell, S. T., J. Lerner, R. Nanda, and R. R. Townsend. 2020. Financial Distancing: How Venture Capital Follows the Economy Down and Curtails Innovation. *NBER*. Working paper.

Huyghebaert, N. 2006. "On the Determinants and Dynamics of Trade Credit Use: Empirical Evidence from Business Start-Ups." *Journal of Business Finance & Accounting* 33 (1-2): 305–328. https://doi.org/10.1111/j.1468-5957.2006.001364.x .

Huyghebaert, N., L. Van de Gucht, and C. Van Hulle. 2007. “The Choice Between Bank Debt and Trace Credit in Business Start-Ups.” *Small Business Economics* 29 (4): 435–452. https://doi.org/10.1007/s11187-006-9005-2.

International Energy Agency. 2021. *Net Zero by 2050. A Roadmap for the Global Energy Sector*. Paris.

International Finance Corporation. 2016. *Green Finance: A Bottom-Up Approach to Track Existing Flows*. Washington D.C.

Kalemli-Ozcan, S., B. Sorensen, C. Villegas-Sanchez, V. Volosovych, and S. Yesiltas How to Construct Nationally Representative Firm Level Data from the Orbis Global Database: New Facts and Aggregate Implications . 2015. *NBER Working Paper series (No. W21558)*.

Kaplan, S. N., and P. Stromberg. 2001. “Venture Capitalists as Principals: Contracting, Screening, and Monitoring.” *The American Economic Review* 91:426–430. https://doi.org/10.1257/aer.91.2.426.

Kaplan, S. N., P. Strömberg, and B. A. Sensoy. 2002. How Well Do Venture Capital Databases Reflect Actual Investments? University of Chicago Unpublished working paper.

Kortum, S., and J. Lerner. 2000. “Assessing the Impact of Venture Capital on Innovation.” *The Rand Journal of Economics* 31 (4): 674. https://doi.org/10.2307/2696354 .

Kortum, S., and J. Lerner. 2001. *Does Venture Capital Spur Innovation?*. Bingley: Emerald Group Publishing Limited.

Kuckertz, A., E. S. Berger, and A. Gaudig. 2019. “Responding to the Greatest Challenges? Value Creation in Ecological Startups.” *Journal of Cleaner Production* 230:1138–1147. https://doi.org/10.1016/j.jclepro.2019.05.149.

Lahr, H., and A. Mina. 2016. “Venture Capital Investments and the Technological Performance of Portfolio Firms.” *Research Policy* 45 (1): 303–318. https://doi.org/10.1016/j.respol.2015.10.001.

Lerner, J. 2002. Boom and Bust in the Venture Capital Industry and the Impact on Innovation. Available at SSRN 366041.

Leuven, E., and B. Sianesi. 2003. “PSMATCH2: Stata Module to Perform Full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing Statistical Software Components S432001.”

Mann, R. J., and T. W. Sager. 2007. “Patents, Venture Capital, and Software Start-Ups.” *Research Policy* 36 (2): 193–208. https://doi.org/10.1016/j.respol.2006.10.002.

Maula, M. V., T. Keil, and S. A. Zahra. 2013. “Top Management’s Attention to Discontinuous Technological Change: Corporate Venture Capital as an Alert Mechanism.” *Organization Science* 24 (3): 926–947. https://doi.org/10.1287/orsc.1120.0775.

Mazzucato, M., and G. Semieniuk. 2018. “Financing Renewable Energy: Who is Financing What and Why It Matters.” *Technological Forecasting & Social Change* 127:8–22. https://doi.org/10.1016/j.techfore.2017.05.021.

Moore, C. B., G. T. Payne, R. G. Bell, and J. L. Davis. 2015. “Institutional Distance and Cross-Border Venture Capital Investment Flows.” *Journal of Small Business Management* 53 (2): 482–500. https://doi.org/10.1111/jsbm.12079 .

Moraes Silva, D. R. D., L. O. Lucas, and N. S. Vonortas. 2020. “Internal Barriers to Innovation and University-Industry Cooperation Among Technology-Based SMEs in Brazil.” *Industry & Innovation* 27 (3): 235–263. https://doi.org/10.1080/13662716.2019.1576507.

Morrison, G., M. Riccaboni, and F. Pammolli. 2017. “Disambiguation of Patent Inventors and Assignees Using High-Resolution Geolocation Data.” *Scientific Data* 4 (1): 1–21.

Mrkajic, B., S. Murtinu, and V. G. Scalera. 2019. “Is Green the New Gold? Venture Capital and Green Entrepreneurship.” *Small Business Economics* 52 (4): 929–950. https://doi.org/10.1007/s11187-017-9943-x.

Munari, F., and L. Toschi. 2015. “Do Patents Affect VC Financing? Empirical Evidence from the Nanotechnology Sector.” *International Entrepreneurship & Management Journal* 11 (3): 623–644. https://doi.org/10.1007/s11365-013-0295-y.

Murtinu, S. 2021. “The Government Whispering to Entrepreneurs: Public Venture Capital, Policy Shifts, and Firm Productivity.” *Strategic Entrepreneurship Journal* 15 (2): 279–308. https://doi.org/10.1002/sej.1374.

Nepelski, D., G. Piroli, and G. De Prato. 2016. European Start-Up Hotspots: An Analysis Based on VC-Backed Companies. Joint Research Centre, JRC Scientific and Policy Report. EUR, 28021.
Oster, E. 2019. "Unobservable Selection and Coefficient Stability: Theory and Evidence." *Journal of Business & Economic Statistics* 37 (2): 187–204. https://doi.org/10.1080/07350015.2016.1227711.
Pasimeni, F. 2019. "SQL Query to Increase Data Accuracy and Completeness in PATSTAT." *World Patent Information* 57:1–7. https://doi.org/10.1016/j.wpi.2019.02.001 .
Pasimeni, F., and A. Fiorini. 2017. "SETIS Database: Data Management for R&I Key Performance Indicators." In *EUR 28853*. Luxembourg: EN, Publications Office of the European Union. https://doi.org/10.2760/37901 .
Pasimeni, F., A. Fiorini, and A. Georgakaki. 2019. Assessing Private R&D Spending in Europe for Climate Change Mitigation Technologies via Patent Data. *World Patent Information*, 59, 101927.
Pasimeni, F., A. Fiorini, and A. Georgakaki. 2021. "International Landscape of the Inventive Activity on Climate Change Mitigation Technologies. A Patent Analysis." *Energy Strategy Reviews* 36:100677. https://doi.org/10.1016/j.esr.2021.100677.
Pasimeni, F., and A. Georgakaki. 2020. Patent-Based Indicators: Main Concepts and Data Availability. JRC121685. https://setis.ec.europa.eu/patent-based-indicators-main-concepts-and-data-availability_en.
Popov, A., and P. Roosenboom. 2012. "Venture Capital and Patented Innovation: Evidence from Europe." *Economic Policy* 27 (71): 447–482. https://doi.org/10.1111/j.1468-0327.2012.00290.x.
Popp, D., and R. Newell. 2012. "Where Does Energy R&D Come From? Examining Crowding Out from Energy R&D." *Energy Economics* 34 (4): 980–991. https://doi.org/10.1016/j.eneco.2011.07.001.
Roma, P., M. Vasi, and C. Kolympiris. 2021. "On the Signaling Effect of Reward-Based Crowdfunding: (when) Do Later Stage Venture Capitalists Rely More on the Crowd Than Their Peers?" *Research Policy* 50 (6): 104267. https://doi.org/10.1016/j.respol.2021.104267.
Sichelman, T., and S. J. Graham. 2010. "Patenting by Entrepreneurs: An Empirical Study." *Michigan Telecommunications and Technology Law Review* 17 111 :.
Thoma, G., S. Torrisi, A. Gambardella, D. Guellec, B. Hall, and D. Harhoff. 2010. Harmonizing and Combining Large Datasets - an Application to Firm-Level Patent and Accounting Data (Issue 15851). National Bureau of Economic Research, Inc. https://www.nber.org/papers/w15851 .
Van Osnabrugge, M., and R. J. Robinson. 2000. *Angel Investing: Matching Startup Funds with Startup Companies–The Guide for Entrepreneurs and Individual Investors*. San Francisco: John Wiley & Sons.
van Pottelsberghe de la Potterie, B., and D. François. 2009. "The Cost Factor in Patent Systems." *Journal of Industry Competition and Trade* 9 (4): 329–355. https://doi.org/10.1007/s10842-008-0033-2.
World Economic Forum. 2020. Community Paper, Bridging the Gap in European Scale-Up Funding: The Green Imperative in an Unprecedented Time, http://www3.weforum.org/docs/WEF_Bridging_the_Gap_in_European_Scale_up_Funding_2020.pdf.
Zhang, L., Y. Guo, and G. Sun. 2019. "How Patent Signals Affect Venture Capital: The Evidence of Bio-Pharmaceutical Start-Ups in China." *Technological Forecasting & Social Change* 145:93–104. https://doi.org/10.1016/j.techfore.2019.05.013.
Zhang, W., Y. G. Jing, and J. Wang. 2015. "Greenization of Venture Capital and Green Innovation of Chinese Entity Industry." *Ecological Indicators* 51:31–41. https://doi.org/10.1016/j.ecolind.2014.10.025.
Zhou, H., P. G. Sandner, S. L. Martinelli, and J. H. Block. 2016. "Patents, Trademarks, and Their Complementarity in Venture Capital Funding." *Technovation* 47:14–22. https://doi.org/10.1016/j.technovation.2015.11.005.

Appendices

Table A1. Definition of variables.

Variable	Definition
VC	An indicator variable that takes the value of 1 if the firm receives Venture Capital funding and 0 otherwise (i.e. receive other equity financing)
VC broad	An indicator variable that takes the value of 1 if the firm receives Venture Capital funding according to our broader definition (i.e. also including Business Angel, CVC, Venture Leasing, Venture Recapitalization) and 0 otherwise (i.e. receive other equity financing)
GreenPat	An indicator variable that takes the value of 1 if the firm holds at least one green patent according to our classification at the year of VC (or other equity) funding, and 0 otherwise
OtherPat	An indicator variable that takes the value of 1 if the firm's patents portfolio contains non-green patents only at the year of the VC funding and 0 otherwise
GreenPatRatio	A continuous variable that measures the ratio between the number of green and total patents that a company holds the year before obtaining VC financing
TotPat	A continuous variable that measures the number of registered patents. It is expressed in natural logarithm
Assets	Natural logarithm of the total assets of the firm
Age	A continuous variable that measures the years since its establishment. It is expressed in natural logarithm
Leverage	A continuous variable that measures the firm's financial indebtedness, constructed as the ratio between the firm's Long-term Debt plus Loans scaled by Total Assets
R&D	An indicator variable that takes the value of 1 if the firm develops activities of research and development, and 0 otherwise
Sector	Industrial sectors of activity of the firms based on NACE 2-digit sector classification
Country	Country of origin of the firm
Green Macro Sectors	An indicator variable that takes the values of 1 if a firm operates in a 'green macro-sectors', represented by those NACE2 broad sectors with at least one firm holding any green patent.
Green Micro Sectors	An indicator variable that takes the values of 1 if a firm operates in a 'green micro-sectors', represented by those 4-digit sectors with at least one firm holding any green patent.

Table A2. Correlation matrix.

	VC	Total Assets	Age	Leverage	R&D	Tot Patents
VC	1.0000					
Total Assets	−0.2985	1.0000				
Age	−0.4003	0.5486	1.0000			
Leverage	0.0129	−0.1262	−0.0595	1.0000		
R&D	0.0064	0.0922	0.0561	0.0198	1.0000	
Tot Patents	0.0880	0.0313	0.0303	0.0559	0.1138	1.0000

Table A3. Baseline model on full sample with continuous variables.

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	VC = 1	VC = 1	VC = 1	VC = 1	VC = 1
Panel A – Probit Estimation					
Non-green patents	0.258***	0.249***	0.229***	0.196***	0.216***
	(0.036)	(0.036)	(0.037)	(0.039)	(0.039)
Green Patents	0.258***	0.259***	0.230***	0.189**	0.229**
	(0.088)	(0.089)	(0.089)	(0.088)	(0.090)
Assets	−0.085***	−0.088***	−0.073***	−0.080***	−0.083***
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
Age	−0.654***	−0.653***	−0.633***	−0.646***	−0.652***
	(0.027)	(0.027)	(0.029)	(0.030)	(0.031)
Leverage	−0.125**	−0.132**	−0.129**	−0.228***	−0.229***
	(0.055)	(0.055)	(0.057)	(0.061)	(0.062)
R&D volumes	0.564	0.569	0.598	0.604	0.654
	(0.519)	(0.514)	(0.502)	(0.511)	(0.515)
Observations	5,775	5,775	5,775	5,775	5,775
Controls	Yes	Yes	Yes	Yes	Yes
Year	No	Yes	Yes	Yes	Yes
Sector	No	No	Yes	Yes	Yes
Country	No	No	No	Yes	Yes
Sector x Country	No	No	No	No	Yes
Panel B – Marginal Effects					
Non-green patents	0.080***	0.076***	0.070***	0.059***	0.064***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)
Green Patents	0.080***	0.079***	0.071***	0.057**	0.068**
	(0.027)	(0.027)	(0.027)	(0.026)	(0.026)
Assets	−0.026***	−0.027***	−0.022***	−0.024***	−0.025***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Age	−0.202***	−0.200***	−0.194***	−0.193***	−0.193***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Leverage	−0.039**	−0.041**	−0.040**	−0.068***	−0.068***
	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)
R&D volumes	0.174	0.174	0.183	0.181	0.193
	(0.160)	(0.157)	(0.154)	(0.153)	(0.152)
Observations	5,775	5,775	5,775	5,775	5,775
Controls	Yes	Yes	Yes	Yes	Yes
Year	No	Yes	Yes	Yes	Yes
Sector	No	No	Yes	Yes	Yes
Country	No	No	No	Yes	Yes
Sector x Country	No	No	No	No	Yes

Notes: The table reports regression results, on the full sample, of the Probit estimation of Equation 1 in Panel A and associated marginal effects in Panel B. The dependent variable is *VC*, an indicator variable that takes the value of 1 if the firm receives Venture Capital funding and 0 otherwise (i.e. receives other equity financing). *Non-green patents* is a continuous variable accounting for the natural logarithm of the number of patents held by the company when funded. *Green patents* is a continuous variable accounting for the natural logarithm of the number of patents held by the company when funded. The vector *Controls* includes four indicators related to the size (*Assets*), the experience (*Age*), the level of debt (*Leverage*), and the attitude towards innovation (*R&D volumes*) of the observed firms (all these indicators included are taken at the year before the funding to avoid simultaneity). To control for shocks common to all firms in different periods of the sample we add year fixed effects. To take account of differences in the VC markets, we also include a set of country and sector fixed effects, while we also introduce their product to control for specific characteristics of sectors across countries. All variables are defined in the text and the Appendix. The table reports coefficient estimates (resp. marginal effects) followed by robust standard errors, clustered at the deal level, in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table A4. Baseline model on matched sample with continuous variables.

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	VC = 1	VC = 1	VC = 1	VC = 1	VC = 1
Panel A – Probit Estimation					
Non-green patents	0.247***	0.237***	0.211***	0.184***	0.211***
	(0.039)	(0.039)	(0.040)	(0.042)	(0.043)
Green Patents	0.322***	0.331***	0.291***	0.254***	0.297***
	(0.089)	(0.090)	(0.090)	(0.090)	(0.090)
Assets	−0.074***	−0.078***	−0.064***	−0.071***	−0.074***
	(0.012)	(0.012)	(0.013)	(0.013)	(0.014)
Age	−0.773***	−0.769***	−0.746***	−0.760***	−0.761***
	(0.032)	(0.032)	(0.034)	(0.036)	(0.037)
Leverage	−0.137**	−0.144**	−0.142**	−0.228***	−0.246***
	(0.060)	(0.060)	(0.063)	(0.067)	(0.068)
R&D volumes	0.505	0.515	0.520	0.505	0.590
	(0.545)	(0.541)	(0.527)	(0.540)	(0.544)
Observations	4,735	4,735	4,735	4,735	4,735
Controls	Yes	Yes	Yes	Yes	Yes
Year	No	Yes	Yes	Yes	Yes
Sector	No	No	Yes	Yes	Yes
Country	No	No	No	Yes	Yes
Sector x Country	No	No	No	No	Yes
Panel B – Marginal Effects					
Non-green patents	0.074***	0.071***	0.063***	0.054***	0.061***
	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)
Green Patents	0.097***	0.098***	0.087***	0.074***	0.086***
	(0.027)	(0.027)	(0.027)	(0.026)	(0.026)
Assets	−0.022***	−0.023***	−0.019***	−0.021***	−0.021***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Age	−0.232***	−0.229***	−0.222***	−0.223***	−0.220***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Leverage	−0.041**	−0.043**	−0.042**	−0.067***	−0.071***
	(0.018)	(0.018)	(0.019)	(0.020)	(0.019)
R&D volumes	0.152	0.153	0.155	0.148	0.171
	(0.163)	(0.161)	(0.157)	(0.158)	(0.157)
Observations	4,735	4,735	4,735	4,735	4,735
Controls	Yes	Yes	Yes	Yes	Yes
Year	No	Yes	Yes	Yes	Yes
Sector	No	No	Yes	Yes	Yes
Country	No	No	No	Yes	Yes
Sector x Country	No	No	No	No	Yes

Notes: The table reports regression results, on the matched sample, of the Probit estimation of Equation 1 in Panel A and associated marginal effects in Panel B. The dependent variable is *VC*, an indicator variable that takes the value of 1 if the firm receives Venture Capital funding and 0 otherwise (i.e. receives other equity financing). *Non-green patents* is a continuous variable accounting for the natural logarithm of the number of patents held by the company when funded. *Green patents* is a continuous variable accounting for the natural logarithm of the number of patents held by the company when funded. The vector *Controls* includes four indicators related to the size (*Assets*), the experience (*Age*), the level of debt (*Leverage*), and the attitude towards innovation (*R&D volumes*) of the observed firms (all these indicators included are taken at the year before the funding to avoid simultaneity). To control for shocks common to all firms in different periods of the sample we add year fixed effects. To take account of differences in the VC markets, we also include a set of country and sector fixed effects, while we also introduce their product to control for specific characteristics of sectors across countries. All variables are defined in the text and the Appendix. The table reports coefficient estimates (resp. marginal effects) followed by robust standard errors, clustered at the deal level, in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table A5. Test for the difference of Green vs Other Patents Probit coefficients and margins.

Test for the difference of Green vs Other Patents margins		
Linear Combination of estimated coefficients	(1)	(2)
Difference (GreenPat – OtherPat)	0.209*	0.061*
	(0.115)	(0.033)
Observations	4,735	4,735
Controls	Yes	Yes
Year	Yes	Yes
Sector	Yes	Yes
Country	Yes	Yes
Sector x Country	Yes	Yes

Notes: The table reports the results of a test for the equality of the coefficients (Col. 1) and the margins (Col. 2) of the main specification of Equation 1, i.e. including the vector *Controls* and all the fixed effects within the matched sample. The table reports the test estimates, followed by robust standard errors, in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.