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PRIVATE EQUITY AND INNOVATION IN THE EURO AREA

by Emanuele Degani*, Simone Letta* and Tommaso Perez*

Abstract

This study examines the relationship between private equity (PE) investments and the innovation capacity of euro area firms, with a special focus on green technologies. Using data on PE deals, patent applications and firm-level characteristics across eight euro area countries from 2010 to 2019, we investigate the link between PE investment and innovation, the latter measured by patent filings. Our findings indicate that firms receiving PE investments increase their patenting activity, with the effect being more pronounced for venture capital (VC) investments. Such a relationship may also stem from the ability of more innovative firms to attract a larger share of PE funding. In this case, PE investors may act as catalysts by amplifying existing innovation potential. With respect to green innovations, the empirical evidence does not indicate a link between innovation and PE investments, possibly due to structural barriers, such as the high risk and the long development cycles, which may have limited PE's ability to drive green technological progress during the sample period.

JEL Classification: C21, O31, Q55.

Keywords: private equity, venture capital, innovation, green patents, sustainability, patent activity.

Sintesi

Questo studio esamina la relazione tra gli investimenti di private equity (PE) e la capacità innovativa delle imprese dell'area dell'euro, con un'attenzione particolare alle tecnologie verdi. Utilizzando dati sulle operazioni di PE, sulle domande di brevetto e sulle caratteristiche delle imprese di otto paesi dell'area dell'euro nel periodo 2010-2019, viene analizzato il legame tra il PE e i contributi innovativi delle imprese, misurati mediante le domande di brevetto. I risultati indicano che le imprese che ricevono investimenti di PE aumentano la produzione di brevetti, con un effetto più pronunciato nel caso di investimenti di venture capital. Tale relazione può derivare anche dalla maggiore capacità delle imprese più innovative di attrarre una quota più elevata di finanziamenti di PE. I fondi di PE possono pertanto agire come catalizzatori, amplificando un potenziale innovativo già esistente. Per quanto riguarda le tecnologie verdi, l'evidenza empirica non segnala un legame tra innovazione e investimenti di PE, probabilmente a causa di barriere strutturali, quali l'elevato rischio e i lunghi cicli di sviluppo, che potrebbero aver limitato la capacità del PE di promuovere il progresso tecnologico verde nel periodo considerato.

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CONTENTS

1 Introduction[1]

Private equity (PE) encompasses investment activities in listed and non-listed firms at different stages of development,[2] ranging from seed or venture capital (VC) initiatives, at the early stage of a firm's development, to the buyout of established firms. PE may provide firms with long-standing support in terms of fresh capital, managerial capabilities, and technical skills (although they may also be occasionally associated with short-term predatory behaviour; Hall,1990; Long and Ravenscraft, 1993). PE can contribute to a firm's development through multiple, possibly complementary, channels: expansion of productive capacity; reaching out to new markets; vertical and horizontal acquisitions; economies of scale and scope; product and process innovation. Our analysis focuses on the support that PE investment can give to the innovation output of target firms.

Innovation is the driving force of economic growth and structural transformation (Schumpeter, 1942). It relies on economic, social and legal substructures supporting entrepreneurship (Porter, 1990). In the EU, the scarcity of private capital investment, especially in the form of venture capital, appears to be one of the main factors behind low productivity growth. The lack of VC investments is particularly acute because of several factors that span from fragmentation of capital markets to low-risk appetite, and to a still insufficient support of governmental institutions towards a favourable environment for the development of a VC ecosystem (Panetta, 2024; Angelini, 2025). Many viable innovations remain commercially unexploited because of the scarcity of innovation 'clusters' that, in the US, along with universities and innovative firms, gather venture capitalists capable of successfully transforming innovative research into marketable products (Draghi, 2024).

Innovation plays a key role in the transition to a green economy, which requires massive development and deployment of new technologies to achieve carbon neutrality (Cervantes *et al.*, 2023). The role of PE investment may be a key element in collecting financial resources with an investment horizon sufficiently long as to allow for an effective transition to a sustainable economic system. In the EU, government-backed institutions channel a non-negligible share of PE investment.[3] The PE industry may contribute to channelling both public and private capital towards climate-friendly investments, with positive interactions between the two sources of funding.

This paper investigates the impact of PE investment on the innovation output of euro area firms, with a focus on innovations that favour the transition to a sustainable economy. Most of the existing empirical literature on the relationship between PE and innovation

[1]The views expressed in this article are our own and do not necessarily represent the views of the Banca d'Italia or the Eurosystem. We would like to thank Gioia Cellai, Francesco Columba, Paolo Del Giovane, Stefano Nobili, Antonio Scalia and Luigi Federico Signorini for their useful suggestions and comments.

[2]We include also listed firms since, in some cases, they are acquired by PE firms and delisted.

[3]For example, the European Investment Fund, Cassa Depositi e Prestiti in Italy, and Caisse des Dépôts et Consignations in France.

refers to two types of PE investment, namely VC (Hirukawa and Ueda, 2008; Lahr and Mina, 2016) and leveraged buyout of established firms (Lerner *et al.*, 2011; Amess *et al.*, 2016). Only a few studies examine firms across multiple European countries, and most of them focus exclusively on VC investments (Popov and Roosenboom, 2012; Faria and Barbosa, 2014; Pradhan *et al.*, 2017). Ughetto (2010) constitutes, to the best of our knowledge, the only exception. Even fewer studies focus specifically on VC activity in Italy. One of the few available contributions is Bronzini *et al.* (2020), which investigates the role of VC in fostering innovation in Italian target firms, among other effects. They found that Italian startups financed by venture capitalists experience a faster growth in size and become more innovative compared with other startups.

In the euro area it is difficult to make a clear distinction between VC and growth funds, as they act at a contiguous stage of a firm's development. In most cases, the distinguishing feature is the size of the deal. This is probably due to the existence of many small and medium PE funds, sometimes under €1 billion of assets under management (AUM), and a few, mainly US-based, large funds operating in the area. Therefore, we decided not to limit the scope of the analysis to VC deals, but to test the possible role of other types of PE investment on the innovation output of target firms.

Since innovation is not directly measurable, we rely on data on patent applications as a proxy for the innovation output of firms, according to the established approach of Griliches (1990). Our analysis is based on a sample of PE deals, including VC deals, occurred in eight EU countries. We collect data from Moody's Orbis – Bureau Van Dijk (henceforth Orbis) database, which links PE investments with target firms and patent applications at the European Patent Office (EPO) through unique identifiers at firm level. As patent applications are published with a considerable lag (typically between 18 and 30 months after their filing date) and given the potential bias introduced by the pandemic on innovation activity, we limit our sample to patent applications filed between 2010 and 2019.[4] To deal with the impact of PE on the transition towards a green economy, we identify a subsample of 'green patents', defined as those relating to any technology potentially able to reduce the negative impacts on the environment of production activities or to improve an efficient use of resources (Favot *et al.*, 2023).

Our main findings point to a significant relationship between PE investments and innovation activity among euro area firms. Statistical inference shows that more than half of the target firms expanded their market share of patenting activity after the intervention of PE, with an increase in the average market share of approximately 43 percent. We further find that this effect is driven primarily by VC investments. Other forms of PE are not found to be significantly associated with patenting activity, though they may con-

[4]Restricting the analysis horizon up to 2019 does not allow capturing the possible effect on innovation due to the growth of private capital observed in more recent years, especially in some countries such as Italy, also driven by the entry of major PE funds.

tribute to firm growth through other means. We also identify a potential signalling effect: firms with already developed innovative capabilities tend to attract a greater proportion of PE funding, suggesting that PE funds can both create the conditions for technological growth in target companies and recognize those with already high innovative potential, acting as catalysts. Regarding green innovation, the evidence is inconclusive. Although patient PE investors could be particularly well-suited to financing high-risk innovations and supporting the transition of brown firms toward sustainability, high uncertainty, long development timelines, and inconsistent green tech policies may limit PE's role in fostering green innovations.

We try to contribute to the empirical literature in two ways. First, we extend our study to the wide category of PE investments, while most of the studies are devoted mainly on VC or, at the other extreme, on leveraged buyouts of listed firms. Second, we provide empirical evidence for the impact of PE investments on innovation by euro area firms, while most existing studies are devoted to the US markets.

2 Review of the empirical literature

PE investment may spur innovation along different avenues, such as increasing R&D productivity (Kortum and Lerner, 2000; Hirukawa and Ueda, 2008; Amess *et al.*, 2016). Furthermore, it may allow young and innovative firms to cross the so-called 'valley of death', an unfavourable business condition that any new enterprise can witness during its early stage of the life cycle. In such circumstances, innovating firms, lacking the necessary financial resources or commercial and managerial competence, may fail to break-even and, eventually, go bankrupt (Gbadegeshin *et al.*, 2022). Still, the impact of private capital investment on innovation is somewhat controversial. Available evidence differs by the type of PE investment under investigation, the period, and the geographical area under coverage. Some empirical evidence suggests that PE investment helps the commercialisation of innovation rather than fostering its creation (Faria and Barbosa, 2014).

The celebrated success stories of firms such as Google, Microsoft, or more recently OpenAI, cannot serve as a blackprint for evaluating the broader impact of VC or PE investments. Both anecdotal and empirical evidence suggest that the contribution of PE – particularly VC – to highly innovative firms in Silicon Valley was tied to a unique set of favourable conditions, including labour mobility, geographical proximity to leading universities, and the presence of venture capitalists that enabled a spatially concentrated learning process (Porter, 1990; Ferrary and Granovetter, 2009; Feldman and Kogler, 2010). Attempts to replicate this model elsewhere, or to identify it in different historical or geographical contexts, are therefore likely to fail (Feldman and Kogler, 2010). This reflects the broader difficulty of extending empirical results obtained for firms in one particular setting (e.g., the US in a given period) to other regions or timeframes.

Innovation outcomes depend on a complex interplay between investment-specific factors (such as the innovative capabilities already accumulated in target firms and the skills of PE investors) and locational characteristics (such as the availability of skilled labour or cultural proximity between target firms and investors). In the EU context, barriers to entrepreneurship, an unfavourable tax and regulatory framework, high capital gains taxation, and both locational and cultural distance between target and receiving firms may further constrain the innovative potential of VC investments (Popov and Roosenboom, 2012; Ughetto, 2010).

Venture capitalism is faced with a 'chicken and egg' problem: does VC investment spur innovation ('venture capital first' hypothesis) or do venture capitalists target firms that already show above-average innovative capabilities ('innovation first' hypothesis)? Several empirical studies tend to confirm this second hypothesis. Venture capitalists invest more on firms that already show above-average patent activity (Engel and Keilbach, 2007; Hellmann and Puri, 2000; Geronikolaou and Papachristou, 2012; Lahr and Mina, 2016). However, the attractiveness of innovative firms for VC investors depends both on the type of innovation signalled by the firm through patenting and the skills of the 'receiver' of the information, i.e. the venture capitalist.[5] More 'reputable' VC investors are more likely to target disruptive innovation and young firms, as they are equipped to handle the risk of failure, which disruptive technologies bring with them (Colombo *et al.*, 2023).

The so-called chicken-and-egg problem between venture capital (VC) investment and innovation should not be overstated. Establishing the direction of causality is inherently difficult, as VC investments – particularly in young firms – tend to occur incrementally, with investors progressively increasing their financial commitment as firms demonstrate results (Jang and Kaplan, 2025). Moreover, the observation that, ceteris paribus, private equity investors are more likely to select highly innovative firms does not undermine the positive contribution of venture capital to the real economy. Rather, it points to a positive screening effect by private market participants, who – owing to greater risk-bearing capacities and stronger incentives than banks – might be better positioned to identify and finance innovative but riskier firms (Cera *et al.*, 2025).

Rather than a linear causation mechanism flowing unidirectionally from VC to innovation, or vice versa, the evidence suggests the existence of a dynamic system in which the two forces interact and reinforce one another. VC may enhance firms' ability to extract value from their technological capabilities by rationalizing technology search processes (Lahr and Mina, 2016), focusing innovative efforts on core competencies (Lerner *et al.*, 2011), and in some cases even reducing R&D expenditures without impairing overall performance (Long and Ravenscraft, 1993). Importantly, there is no counterfactual evidence

[5] More generally, VC investors tend to evaluate a number of aspects of target firms such as team, market, product and innovation, and exit characteristics to select their investments (Jang and Kaplan, 2025).

to suggest that, in the absence of VC financing, firms would be more likely to overcome the valley of death or other critical stages of development. On the contrary, private equity and venture investors often respond to technological opportunities by transforming them into commercially viable ventures (Hall and Lerner, 2010), thereby shaping the selection of firms that emerge as winners in the evolutionary process of industrial dynamics (Dosi and Nelson, 2010).

Another strand of empirical literature focuses on the relation between PE investment and green innovation. Several factors seem to play a crucial role. When operating in a favourable institutional environment for the development of clean energy technologies ('cleantech'), such as the euro area in the recent decades, firms with patent applications in green technologies have been more likely to attract VC financing (Bellucci *et al.*, 2023). Under alternative circumstances, cleantech may become unattractive for venture capitalists because of the heavy reliance on unstable (especially in the US) governmental support and the inherent features of this industry, that limit the upside potential of the investment: in the cleantech sector it is unlikely that a winner will take all, as it often happens in the IT or biotech sectors (Van den Heuvel and Popp, 2023). Furthermore, PE deals in green technologies may be hindered by the scarcity of exit opportunities in the form of Initial Public Offerings or other PE funds able to replace or co-invest with the previous PE investor with sufficient size to scale up investment opportunities (De Haan Montes *et al.*, 2023). Finally, even in a favourable institutional environment like the euro area, there may be different technological specializations across countries, such that those with a historically broader and more developed 'cleantech' sector tend to generate a higher number of green patents (Lotti and Nobile, 2025).

3 Data and preliminary analysis

Data scarcity, inherently associated with the private nature of PE investments, constitutes the major problem in empirical research on this segment of the financial market. Problems are particularly severe when data on PE investment are matched with other kinds of firm-level data, such as patenting activity. Our empirical analysis relies on the Orbis database. It includes three sections collecting data on firms, patents ('Orbis Intellectual Property'), and deals ('Orbis M&A', previously known as 'Zephyr'), respectively. A unique firm-level identifier connects the three sections.

3.1 Firms

We consider nonfinancial firms[6] headquartered in eight euro area countries that represent the largest economies in the euro area, namely Austria, Belgium, France, Germany, Italy, the Netherlands, Portugal, and Spain. We exclude micro-firms.[7] In the absence of dimensional variables (employees, balance sheet size) for some jurisdictions, we also rely on the proprietary Orbis size classification. In particular, the problem of missing dimensional data in the Orbis database is severe for French firms as the national legislation allows small firms to maintain confidentiality. The use of the Orbis size classification partially addresses this gap.

3.2 Patents

Patent applications from the EPO are published with a considerable lag (between 18 and 30 months after their filing; see, for instance, Bellucci *et al.*, 2023). Furthermore, patent granting for successful applications involves a variable processing time. These issues and the likely influence of the pandemic period led us to restrict our sample from 2010 to 2019 and to use patent application filings as an indicator of innovation activity. Admittedly, counting patent application filings can bring an overestimation of innovation activity: after a patent application is filed, the patent is granted if it passes a scrutiny regarding novelty and potential utility, while most of the patents filed fail the test (Griliches, 1990). However, our aim is not to provide an absolute measure of innovation activity by target firms. Rather, we are interested in assessing the changes in innovative efforts – whether incremental or decremental – undertaken by firms after receiving investment from PE firms, following a practice widely adopted in the literature(Geronikolaou and Papachristou, 2012; Faria and Barbosa, 2014; Bellucci *et al.*, 2023).

In addition to measuring the innovative activity of a target firm as a whole, we are interested in evaluating its 'green' innovation activity. Following Favot *et al.* (2023), each patent has been classified as green if at least one of the classification schemes ENV-TECH (developed by the OECD), IPC Green Inventory (developed by the WIPO), or Y02/Y04S Tagging scheme (developed by the EPO) categorises one of its IPC and/or CPC codes,

[6]We also exclude real estate sectors. Therefore, the exclusions relate to sectors K and L according to Nace Rev. 2 classification.

[7]Firms with less than 10 employees and a turnover or balance sheet total of up to €2 million according to EU classification. The exclusion of micro firms is motivated by the fact that this Orbis classification includes a large number of sole proprietorships with data of questionable reliability, which may introduce noise into the results of the analysis. However, we acknowledge that this choice may lead to the exclusion of many start-ups, which are potentially targets of VC investments. This concern is partly mitigated by the fact that, while start-ups are by definition micro at inception, many grow rapidly after receiving investment and are no longer classified as micro. Since our classification relies on the most recent available Orbis data (end of 2019 or preceding years), the exclusion of micro firms may have omitted some start-ups that remained micro throughout the decade. At the same time, a considerable number of start-ups – particularly among targets – grew to 'small' or 'medium' size during the decade and were therefore included in the analysis.

both primary or secondary, as green.[8] Indeed, the three classification schemes tend to complement each other in identifying those patents related to environmentally friendly technologies, i.e., those that can contribute to the reduction of negative impacts on the environment of existing human activities and/or promote more efficient use of resources.[9]

3.3 PE transactions

We collect data on PE transactions, including VC ones, which have affected the firms in the sample over the 2010-2019 period. This choice allows us to broaden our area of investigation beyond the narrow (at least in the euro area) scope of VC. Indeed, the euro area landscape is dominated by a large number of small and medium enterprises, small to medium PE firms (typically under €1 billion of AUM), and a few (mainly US-based) large ones operating in the area. Thus, the most prominent feature among PE investments tends to be the size of the target firms (and consequently of the PE deals) instead of the stage of development of the target firms. Furthermore, venture and growth funds tend to act at very contiguous stages of a firm's development.

3.4 Exploratory data analysis

After some pre-processing of the data[10] to deal with duplications and missing information, we obtain a sample of 1,783,889 firms, 3,805,163 patent application filings (of which 16% refers to green patents), and 9,271 PE transactions (of which 37% classified as VC). The latter have involved 6,976 target firms.[11] Firms not involved in PE deals constitute the control group, while those involved represent the treatment group. The control group appears as fairly representative of the relative economic weight of countries, with the notable exception of France, which is underweighted in terms of the number of firms due to the absence of data on individual firms, as mentioned earlier (table 1, column I). Conversely, France is overweighted in the treatment group (column VI) as the largest PE players in the euro area are headquartered in France (while the largest European players are, outside the euro area, in Switzerland and the UK). Although Italian firms in the control group outnumber their French and Dutch counterparts, their volume of patent applications (including the green ones) is lower than in the other two countries

[8] IPC stands for the International Patent Classification and CPC for the Cooperative Patent Classification.

[9] Favot *et al.* (2023) provide a detailed illustration of the three different classification schemes, which suggests the opportunity to use them in combination to enrich the information set of green classifications.

[10] The full sequence of steps, from data acquisition via Orbis to their assembly and preprocessing, is described in detail in Appendix A.

[11] In the case of firms involved in multiple PE agreements within the same year, only the agreement with the earliest completion date (i.e., the first one concluded during the year) has been recorded. This simplification aligns with the objectives of the analysis and is based on the assumption – validated by a sample review of such cases – that multiple PE agreements targeting the same firm in the same year are often 'tranches' of a single agreement with the same counterparties.

(columns II, III). In the treatment group, the share of patent applications filed by Italian firms increases (column VII), particularly in the green segment (column VIII). Except for Austria, the patent intensity of firms targeted by PE investment is much higher than in the control group (column IX vs column IV). The same (in this case including Austria) applies for green patents (column X vs column V).

Most firms belong to sectors G (Wholesale and retail trade; repair of motor vehicles and motorcycles), C (Manufacturing), F (Construction), and M (Professional, scientific and technical activities) (table 2, column I); one of them, F, is much less represented when considering firms involved in a PE agreement, while sector J (Information and communication) stands out (column VI). In terms of patent applications (columns II and VII), including green patents (columns III, VIII), the sectors where production is concentrated, even in relation to the number of firms (columns IV, V, IX and X), are C and M.

PE deals show an increasing trend during the sample period, driven primarily by the growth of new VC investments (table 3). Over time, countries previously trailing in terms of PE deals, such as Italy, have narrowed the gap with countries like France, where the PE industry was already well established (table 4). Patent applications filed by target firms (Treatment group) have grown over the years. However, the share of green patent applications has slightly decreased over time, which is somewhat counterintuitive in view of the increasing pressure of the policies in favour of climate transition (table 5).

Table 1

Firms and patent application filings by country

Country	Control group					Treatment group				
	I	II	III	IV	V	VI	VII	VIII	IX	X
	Firms (%)	Patent applications (%)	Green patent applications (%)	Patent applications per firm	Green patent applications per firm	Firms (%)	Patent applications (%)	Green patent applications (%)	Patent applications per firm	Green patent applications per firm
Austria	3.3	3.3	3.2	2.1	0.3	1.5	1.7	1.1	26.7	2.6
Belgium	4.2	3.3	3.6	1.6	0.3	5.3	7.5	8.7	32.5	5.8
France	14.6	21.5	21.5	3.0	0.5	36.6	28.6	21.4	18.0	2.1
Germany	26.9	52.0	57.6	4.0	0.7	21.1	44.9	57.5	49.2	9.8
Italy	23.6	8.4	4.9	0.7	0.1	10.7	9.6	6.5	20.9	2.2
Netherlands	7.6	8.9	6.7	2.4	0.3	9.4	3.3	2.5	8.1	1.0
Portugal	4.6	0.2	0.2	0.1	0.0	2.3	0.3	0.4	3.4	0.5
Spain	15.4	2.3	2.3	0.3	0.0	13.0	4.0	2.0	7.1	0.5
Total	100	100	100	2.1	0.3	100	100	100	23.1	3.6

Source: Orbis; own elaborations.

Table 2

Firms and patent application filings by sector

Sector	Control group					Treatment group				
	I	II	III	IV	V	VI	VII	VIII	IX	X
	Firms (%)	Patent applications (%)	Green patent applications (%)	Patent applications per firm	Green patent applications per firm	Firms (%)	Patent applications (%)	Green patent applications (%)	Patent applications per firm	Green patent applications per firm
A	2.8	0.2	0.2	0.1	0.0	0.3	0.3	0.3	19.1	3.0
B	0.3	0.5	1.2	4.1	1.4	0.1	0.1	0.2	24.0	6.1
C	15.7	70.4	70.1	9.2	1.4	24.4	60.0	63.9	56.8	9.4
D	1.5	0.6	0.9	0.8	0.2	1.6	0.2	0.5	2.4	1.2
E	0.8	0.1	0.5	0.4	0.2	0.5	0.1	0.5	5.2	3.0
F	13.9	0.5	0.6	0.1	0.0	2.0	0.2	0.5	1.8	0.9
G	24.2	4.9	2.6	0.4	0.0	13.4	5.9	3.9	10.1	1.0
H	5.1	0.2	0.2	0.1	0.0	2.1	0.3	0.1	3.1	0.1
I	6.6	0.0	0.1	0.0	0.0	1.5	0.0	-	0.1	-
J	3.5	1.9	0.6	1.1	0.1	27.6	3.1	1.0	2.6	0.1
M	10.3	17.0	19.1	3.4	0.6	17.1	28.5	28.6	38.6	6.0
N	6.6	2.1	1.6	0.7	0.1	5.3	0.8	0.3	3.3	0.2
O	0.2	0.0	0.0	0.1	0.0	-	-	-	-	-
P	1.2	0.6	0.8	1.1	0.2	1.0	0.0	-	0.2	-
Q	4.4	0.4	0.2	0.2	0.0	1.5	0.6	0.3	9.0	0.6
R	1.5	0.0	0.0	0.0	0.0	0.8	0.0	0.0	0.4	0.0
S	1.6	0.4	1.4	0.5	0.3	0.8	0.1	0.1	2.4	0.4
T	0.0	0.0	-	0.1	-	-	-	-	-	-
U	0.0	0.0	-	0.0	-	-	-	-	-	-
Total	100	100	100	2.1	0.3	100	100	100	23.1	3.6

Source: Orbis; own elaborations.
Notes. '0.0' indicates a percentage strictly lower than 0.05%; '-' means 0%. The sectoral classification is based on the NACE Rev. 2 classification. A=Agriculture, forestry and fishing; B=Mining and quarrying; C=Manufacturing; D=Electricity, gas, steam and air conditioning supply; E=Water supply; sewerage, waste management and remediation activities; F=Construction; G=Wholesale and retail trade; repair of motor vehicles and motorcycles; H=Transportation and storage; I=Accommodation and food service activities; J=Information and communication; M=Professional, scientific and technical activities; N=Administrative and support service activities; O=Public administration and defence; compulsory social security; P=Education; Q=Human health and social work activities; R=Arts, entertainment and recreation; S=Other service activities; T=Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use; U=Activities of extraterritorial organisations and bodies.

Table 3

Private equity deals

Deal year	Deals (#)	Share of VC deals (%)
2010	525	25.0
2011	571	29.4
2012	625	27.8
2013	680	36.2
2014	869	35.2
2015	1,059	39.3
2016	1,077	46.2
2017	1,160	40.6
2018	1,367	43.2
2019	1,338	35.2
Total	9,271	37.5

Source: Orbis; own elaborations.

Table 4

Private equity deal trend by country

(per cent)

Country	Year										
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
Austria	1.3	1.1	1.0	2.2	1.3	1.6	2.6	0.9	1.7	0.6	1.4
Belgium	5.9	4.4	2.9	4.4	4.4	5.8	5.6	4.8	6.1	4.9	5.1
France	45.0	39.9	46.7	35.0	36.4	35.5	33.7	36.0	33.5	33.1	36.3
Germany	21.0	23.5	22.4	23.1	22.7	22.1	24.0	22.9	23.7	22.9	22.9
Italy	7.0	7.4	7.5	10.0	9.8	9.1	9.4	10.9	11.6	12.9	10.1
Netherlands	6.7	10.7	9.3	8.7	11.2	9.1	8.3	8.7	7.2	8.8	8.8
Portugal	2.3	1.1	1.1	2.9	2.3	2.5	1.8	1.5	2.0	2.5	2.0
Spain	10.9	12.1	9.1	13.7	12.1	14.4	14.7	14.1	14.1	14.3	13.4
Total	100	100	100	100	100	100	100	100	100	100	100

Source: Orbis; own elaborations.

Table 5

Patent application filings by target firms

Filing year	Filings (#)	Share of green patents (%)
2010	12,472	15.4
2011	14,307	16.7
2012	14,609	16.6
2013	14,656	17.8
2014	15,052	16.1
2015	17,140	16.3
2016	19,267	14.9
2017	17,679	14.1
2018	18,752	14.2
2019	17,303	14.4
Total	161,237	15.5

Source: Orbis; own elaborations.

3.5 Statistical inference

An observed rise in the absolute number of patent applications may simply reflect a general market trend rather than the effect of PE transactions. We therefore test whether PE investment is associated with an increase in the relative share of patenting activity by PE-backed firms compared to their peers. To preliminarily test this hypothesis, we compute the market share in terms of patent applications filed for each firm, before (pre-deal market share) and after (post-deal market share) the calendar year in which the PE deal occurred.[12]

Let $PatentApplications_{i,t}$ be the number of patent applications filed by firm i in year t, and $DealYear_i$ be the year in which the PE deal involving firm i was finalised (if the firm was involved in multiple deals over the decade, only the earliest year is considered assuming it is the most significant). Eqs. 1 and 2 show the calculations of the pre- and post-deal market shares of patent applications filed by the i-th firm, out of a total of N firms. Furthermore, as the effects of PE investment may show up with a time lag – reflecting the period required for investors to enhance the innovative output of target firms – we introduced a time-delay parameter $\tau \geq 0$ to possibly account for this effect. Taking $\tau = 0$ means interpreting the year in which the PE deal was finalised ($DealYear_i$) as already part of the 'post-deal' life of a firm. Conversely, choosing $\tau = 1$ means computing the 'post-deal' measure starting from the year immediately following ($DealYear_i + 1$) and therefore interpreting the innovation capacity expressed in the year of the PE deal ($DealYear_i$) as still part of the 'pre-deal' life.[13]

$$\pi_{i;\tau}^{pre} = \frac{1}{(DealYear_i + \tau - 2010)} \sum_{t=2010}^{DealYear_i+\tau-1} \frac{PatentApplications_{i,t}}{\sum_{i=1}^{N} PatentApplications_{i,t}}, \qquad (1)$$

$$\text{provided that } DealYear_i \geq 2011$$

$$\pi_{i;\tau}^{post} = \frac{1}{(2019 - (DealYear_i + \tau) + 1)} \sum_{t=DealYear_i+\tau}^{2019} \frac{PatentApplications_{i,t}}{\sum_{i=1}^{N} PatentApplications_{i,t}}, \qquad (2)$$

$$\text{provided that } \quad DealYear_i + \tau \leq 2019$$

[12]For a given firm, its pre-deal (post-deal) market share is the average annual market share over the years before (after) the deal. The annual market share is the number of patent applications filed by a firm in a given year relative to the total number of applications filed by all firms in our sample in that year. The choice to normalize the number of patent applications of a firm, rather than directly considering the absolute number, allows us to neutralise possible spurious effects due to the positive trend in patent application filings observed over the sample period.

[13]Notice $\pi_{i;\tau}^{pre}$ cannot be calculated for all firms whose first agreement ($DealYear_i$) occurred in the year 2010, while $\pi_{i;\tau}^{post}$ cannot be calculated for all firms whose first agreement occurred after the year $2019 - \tau$. The summation from $i = 1$ to N in both equations is intended to be carried out on all the firms (control and treatment groups) having filed at least one patent application in the observed decade.

Eqs. 1 and 2 can also be reformulated for the market shares of green patent applications by replacing $PatentApplications_{it}$ with $GreenPatentApplications_{it}$, the latter being the number of green patent applications filed by firm i in calendar year t. We denote these additional measures as $\varpi_{i;\tau}^{pre}$ and $\varpi_{i;\tau}^{post}$, respectively. For a given firm i, if $\pi_{i;\tau}^{post} > \pi_{i;\tau}^{pre}$ (similarly, $\varpi_{i;\tau}^{post} > \varpi_{i;\tau}^{pre}$) the market share of patent applications (similarly, green patent applications) increased after the PE deal. This would reflect a positive contribution of PE to the innovative capacity of firm i.

The comparison between distributions of pre-deal and post-deal measures (Figure 1) suggests a slight median increase, more pronounced for $\tau = 0$ and fading away for $\tau = 1$ and $\tau = 2$, both for the market shares of firms involved in patent applications (sub-panel a) and for the subset of those only involved in green patenting (sub-panel b). The increase in the third quartile of the post-deal distribution is even more pronounced, with $\tau = 0$ showing approximately double the pre-deal measures, for both the entire patent universe and the green patent subset; here too, the increase tends to narrow down for $\tau = 1$ and $\tau = 2$, suggesting that the year in which the PE deal occurred and those immediately following are more significant in achieving a superior innovation capacity. Table 6 reports summary statistics about the impact of PE on innovation activity: when $\tau = 0$, more than half of the firms experienced an increase in the market share for both their overall patenting (60.7%) and green patenting (62.8%), with a relative increase in the average market share of approximately 43% (50% for green patenting).[14] This positive effect tends to vanish if the year in which the PE deal occurred and possibly its subsequent year are still part of the 'pre-deal' life of a firm ($\tau = 1, 2$).

The evidence of an increase in the post-deal market share for all patents is supported by inferential conclusions drawn from statistical tests, which also consider the sample size. The increase in the market share of patents is statistically significant for the vast majority of countries and sectors (table 7). However, significance tends to diminish with $\tau = 1$ and nearly disappears at $\tau = 2$, supporting previous graphical evidences. With respect to the subset of green patents (table 8), the significance is limited to a few countries or sectors starting from the year of the agreement ($\tau = 0$).

All inferential analyses presented so far preliminarily explored the presence (and the sign) of a link between PE and a firm's innovative capacity, while accounting for the influence of the year in which the PE deal concludes and the immediately following years. In the following section, the existence of this link will be measured employing more advanced and methodologically appropriate statistical techniques, which will also allow us to assess its magnitude while considering the temporal structure of the data.

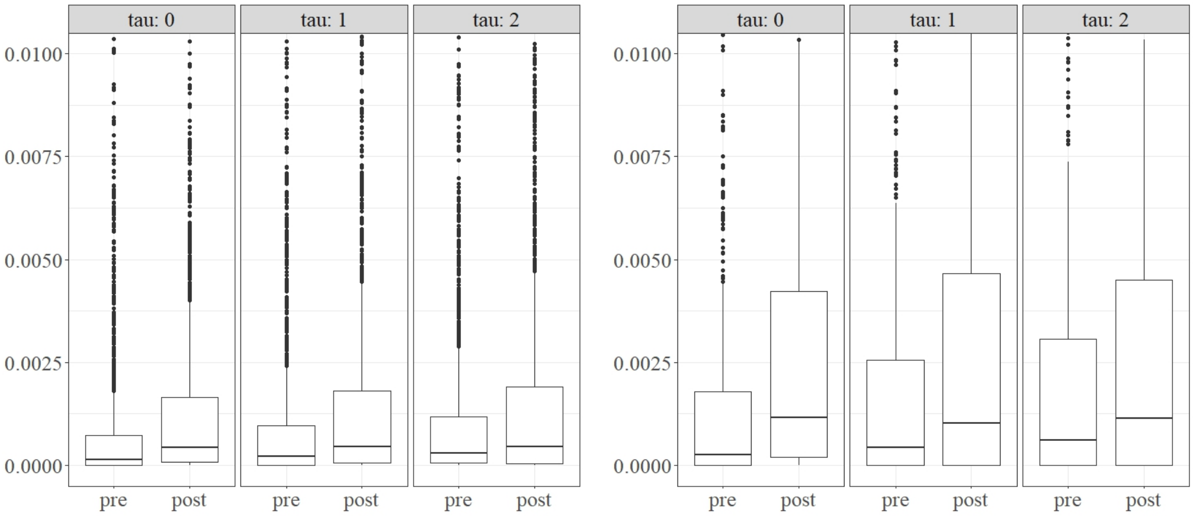
[14]Notice the distributions are highly skewed, and therefore their first moment does not fully capture the shape of the distribution. For this reason, we have depicted the full shape of the distributions in Figure 1, summarizing a set of characteristic percentiles.

Figure 1

Pre- and post-deal market share distributions

(per cent)

(a) All patents (π_τ^{pre} and π_τ^{post}) (b) Green patents (ϖ_τ^{pre} and $\varpi_\tau^{\text{post}}$)



Source: Orbis; own elaborations.

Notes. Each boxplot summarizes the market share distribution: the box spans from the first quartile to the third quartile of the distribution, and the line inside the box marks the median. Whiskers extend to the smallest and largest values within 1.5 × (third quartile − first quartile) from the quartiles; points beyond the whiskers indicate 'outlier' observations. All firms with both pre- and post-deal market shares equal to zero were excluded from the graph, i.e., firms that did not file any patent applications during the considered decade, reasonably assuming that the activities of such firms do not involve the publication of patents. To ensure fair comparability between the distributions of pre- and post-deal measures with an equal number of firms, all firms with unavailable pre-deal or post-deal measures were also excluded from the plotted distributions. The vertical axis was restricted to visually facilitate the comparison of the distribution mass, excluding a relatively small number of outliers with highly extreme market shares.

Table 6

Impact of PE on innovation activity

(per cent)

	$\tau = 0$			$\tau = 1$			$\tau = 2$		
All patents									
Sample size (#)	1,828			1,808			1,602		
% of firms with $\pi^{post} > \pi^{pre}$	60.7			57.5			51.9		
	π^{pre}	π^{post}	Δ% post-pre	π^{pre}	π^{post}	Δ% post-pre	π^{pre}	π^{post}	Δ% post-pre
Sample mean	0.0013	0.0018	42.6	0.0020	0.0025	25.0	0.0022	0.0026	17.5
Green patents									
Sample size (#)	556			573			516		
% of firms with $\varpi^{post} > \varpi^{pre}$	62.8			57.2			52.3		
	ϖ^{pre}	ϖ^{post}	Δ% post-pre	ϖ^{pre}	ϖ^{post}	Δ% post-pre	ϖ^{pre}	ϖ^{post}	Δ% post-pre
Sample mean	0.0033	0.0049	50.2	0.0066	0.0077	16.3	0.0075	0.0078	4.7

Source: Orbis; own elaborations.

Notes: All firms with both pre- and post-deal market shares equal to zero were excluded, i.e., firms that did not file any patent applications during the considered decade, reasonably assuming that the activities of such firms do not involve the publication of patents. To ensure fair comparability between pre- and post-deal measures with an equal number of firms, all firms with unavailable pre-deal or post-deal measures were also excluded.

Table 7

Statistical tests on market share of patents

(p-values)

	τ = 0			τ = 1			τ = 2		
	Binomial sign test	Wilcoxon signed-rank test	Fisher-Pitman permutation test	Binomial sign test	Wilcoxon signed-rank test	Fisher-Pitman permutation test	Binomial sign test	Wilcoxon signed-rank test	Fisher-Pitman permutation test
Total									
	0.00***	0.00***	0.00***	0.00***	0.00***	0.21	0.07*	0.00***	0.20
Aggregation by country									
Austria	0.00***	0.00***	0.09*	0.06*	0.03**	0.13	0.16	0.03**	0.10*
Belgium	0.01***	0.00***	0.10*	0.12	0.01***	0.30	0.42	0.13	0.32
France	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.02**	0.00***	0.00***
Germany	0.00***	0.00***	0.09*	0.02**	0.00***	0.39	0.82	0.11	0.51
Italy	0.01***	0.00***	0.19	0.02**	0.00***	0.26	0.12	0.00***	0.13
Netherland	0.02**	0.00***	0.01***	0.03**	0.01***	0.04**	0.23	0.01***	0.04**
Portugal	0.42	0.18	0.18	0.93	0.76	0.18	0.87	0.76	0.54
Spain	0.00***	0.00***	0.01***	0.02**	0.00***	0.00***	0.65	0.07*	0.01***
Aggregation by sector									
C	0.00***	0.00***	0.01***	0.01***	0.00***	0.40	0.74	0.03**	0.46
G	0.02**	0.00***	0.16	0.00***	0.00***	0.02**	0.07*	0.00***	0.05**
J	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.22	0.00***	0.02**
M	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00	0.00***	0.00***

*: p-value ≤ 0.10, **: p-value ≤ 0.05, ***: p-value ≤ 0.01.

Notes. For the Binomial Sign test, the null hypothesis is that the median difference between paired samples is zero (i.e., an equal probability of positive and negative differences between pre- and post-deal market shares). For the Wilcoxon Signed-Rank test, the null hypothesis is that the median difference between paired samples is zero (the test considers both the sign and the magnitude of the difference). For the Fisher-Pitman Permutation test, the null hypothesis is that the two paired samples are exchangeable (i.e., no systematic differences between them are present). For all the tests, the alternative hypothesis is unidirectionally specified as the post-deal market shares being 'non-parametrically greater' than the pre-deal market shares. Rejecting the null hypothesis hence yields statistical significance in favour of our research question of interest. The sectoral classification is based on the NACE Rev. 2 classification: C=Manufacturing; G=Wholesale and retail trade; J=Information and communication; M=Professional, scientific and technical activities.

Table 8

Statistical tests on market share of green patents

(p-values)

	τ = 0			τ = 1			τ = 2		
	Binomial sign test	Wilcoxon signed-rank test	Fisher-Pitman permutation test	Binomial sign test	Wilcoxon signed-rank test	Fisher-Pitman permutation test	Binomial sign test	Wilcoxon signed-rank test	Fisher-Pitman permutation test
Total									
	0.00***	0.00***	0.00***	0.00***	0.00***	0.30	0.16	0.00***	0.37
Aggregation by country									
Austria	0.21	0.16	0.56	0.85	0.81	0.71	0.85	0.70	0.65
Belgium	0.11	0.05**	0.16	0.43	0.09*	0.28	0.83	0.51	0.36
France	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.01***	0.00***	0.00***
Germany	0.02**	0.02**	0.16	0.12	0.11	0.54	0.72	0.60	0.56
Italy	0.30	0.09*	0.63	0.60	0.15	0.55	0.71	0.20	0.49
Netherland	0.02**	0.03**	0.05**	0.07*	0.03**	0.05**	0.03**	0.02**	0.06*
Portugal	0.36	0.47	0.50	0.64	0.73	0.50	0.86	0.73	0.68
Spain	0.02**	0.01***	0.01***	0.24	0.05**	0.01***	0.85	0.46	0.06*
Aggregation by sector									
C	0.01***	0.00***	0.03**	0.08*	0.00***	0.47	0.58	0.05**	0.51
G	0.12	0.08*	0.41	0.33	0.15	0.29	0.50	0.12	0.46
J	0.00***	0.02**	0.02**	0.08*	0.15	0.14	0.12	0.08*	0.04**
M	0.00***	0.00***	0.05**	0.00***	0.00***	0.03**	0.09*	0.01***	0.08*

Notes. See Table 7 for explanatory notes.

4 Difference-in-differences causal analysis

The evidence in the previous section, while encouraging, does not explicitly account for the time dimension of the data. Instead, it aggregates the market share in patent applications before and after the PE agreement without explicitly taking into account the pre- and post-deal dynamics of patent applications over time. Given the longitudinal nature of the data sample, it is necessary to extend the analysis by adopting an econometric approach designed for intertemporal causal effects.

The analysis of causal effects has undergone significant methodological advancements. The regression discontinuity design (Imbens and Lemieux, 2008) has gained popularity for its ability to identify causal effects by exploiting discontinuities in eligibility rules or thresholds, enabling quasi-experimental comparisons between units just above and below a given cutoff. Another prominent methodology is the synthetic control method (Abadie *et al.*, 2010), particularly useful in contexts with a single or aggregate-level treatment, where control units are constructed as weighted combinations of untreated units to replicate the treated group's pre-treatment trend. Matching techniques and propensity score methods (Rosenbaum and Rubin, 1983) remain essential for creating comparable groups in the absence of natural experiments, though they have recently been complemented by Bayesian approaches and machine learning, which enhance the selection of relevant covariates and group balancing. The growing application of instrumental variables techniques (Angrist and Krueger, 2001), especially combined with longitudinal data, has addressed complex endogeneity issues, further advancing causal identification in real-world economic contexts. Among these, a widely used approach – employed in this section to study the causal effects of PE interventions – is the difference-in-differences (hereafter, DiD) method (Card and Krueger, 1994; Angrist and Pischke, 2009).

4.1 2x2 DiD and its limit in our usecase

In the simplest version of DiD techniques ('2x2 DiD', also known as 'two-period DiD' or 'canonical DiD'), two time points ($t = 1, 2$) and a set of units (indexed by i) are considered, assumed to be drawn from two distinct populations: the 'treatment group' ($D_i = 1$), which receives an exogenously-imposed treatment between the first and second time points, and the 'control group' ($D_i = 0$), which remains untreated in both time points. Let $Y_{i2}(1)$ be the potential outcome for unit i at time point 2 if it undergoes treatment between the two time points and $Y_{i2}(0)$ be the alternative one if it remains untreated at both time points. The quantity of interest is typically the 'average treatment effect on the treated' at time $t = 2$, defined as: $ATT = \mathbb{E}[Y_{i2}(1) - Y_{i2}(0) \mid D_i = 1]$. The main criticality is that only one between $Y_{i2}(1)$ and $Y_{i2}(0)$ is actually observed at $t = 2$, denoted with Y_{i2}. Under the 'no anticipatory effect' and 'parallel trend' assumptions, DiD directly addresses this limit re-expressing the ATT as follows: $ATT = \mathbb{E}[Y_{i2} - Y_{i1} \mid D_i =$

$1] - \mathbb{E}[Y_{i2} - Y_{i1} \mid D_i = 0]$. This latter quantity is therefore estimated given the observed data: if it is significantly different from zero, it implies a causal effect on Y due to the treatment exposure.

DiD techniques align well with our research question: the time points are calendar years, the units are firms, the treatment corresponds to the PE deals (including the subcategory of VC), and the response variable reflects innovation. The latter is approximated by the number of patent applications filed in a specific year. Nonetheless, the 2x2 DiD approach is limited in addressing the richness of our data and the study's objectives for two reasons:

i. the sample firms are observed longitudinally over the decade, and not just over two years. In addition to the year of the PE deal and the immediately preceding year, data is available for years before and after the deal;

ii. PE deals occur in different years for different firms, implying that the observed relationship between PE and innovation may vary in magnitude and direction depending on the year when the treatment (i.e., the deal) is applied.

The first issue could be addressed by considering only on two time points (the year of the deal and the previous year), discarding data from all other years. However, this would limit the analysis by assuming that any increase in innovation due to PE occurs solely in the year of the deal (i.e., immediately after treatment). It is more plausible to expect that such effects, if they exist, might emerge over more years. PE investors might take some time after the agreement to make their contribution in terms of managerial and technological innovation that eventually leads to a patent application increase.[15] The second issue could be handled by conducting several 'independent' 2x2 DiD analyses, each one with the treatment group consisting of firms completing a PE deal in a specific year; this would yield multiple ATT estimates, one for each year. However, it remains unclear how to aggregate these estimates into a comprehensive result.

4.2 Staggered DiD and the Callaway and Sant'Anna (2021) estimator

Recently, a strand of research in the DiD literature has focused on data types like ours named 'staggered DiD' setups, where data spans multiple time periods ($t = 1, 2, \dots, T$). In particular: no units are assumed to be treated at $t = 1$, some of them are treated in potentially different and subsequent time periods and, once treated, they are assumed to

[15] Another issue relates to the fact that, in dealing with yearly data, we do not know whether the deal has been executed at the beginning or at the end of the year. This uncertainty makes it challenging to pinpoint whether any immediate effects of the deal, if they exist, occur within the year of the deal or in the subsequent year.

remain treated forever until T. Notice that the staggered DiD framework embeds 2x2 DiD as a special case if $T = 2$. The key concept here is that each unit has a potential outcome at each time period depending on whether it has already been treated or not and, if treated, on the specific time period t in which it received the treatment. The main challenge lies in estimating these dynamic counterfactual outcomes while accounting for the sequential nature of treatments.

In this study, we adopt the methodology introduced by Callaway and Sant'Anna (2021), which extends the 'no anticipatory effect' and 'parallel trend' assumptions for 2x2 DiD to the aforementioned staggered DiD framework.[16] This approach generalises the ATT to the concept of the 'group-time average treatment effect on the treated', defined as: $ATT(g,t) = \mathbb{E}[Y_{it}(g) - Y_{it}(0) \mid G_{ig} = 1]$. Here G_{ig} is a binary indicator equal to 1 if unit i is first treated at time $g = 2, \ldots, T$ and 0 otherwise. The $ATT(g,t)$ represents the average causal effect on Y at time t for units first treated at time g. In the 2x2 DiD case, $ATT = ATT(2,2)$. With more than two periods, the Callaway and Sant'Anna (2021) method allows for the estimation of, for example, $ATT(2, 2+n)$, i.e. the average effect on units treated at $g = 2$, measured $n \leq T - 2$ time periods after treatment. The same applies to units treated at $g = 3$ ($ATT(3, 3+n)$, for $n \leq T - 3$), $g = 4$, and so on. The method also enables the estimation of pseudo-effects in pre-treatment periods: $ATT(g, g-n)$, for $n \leq g - 1$. These estimates allow to empirically assess whether units first treated at time g exhibit parallel trends with untreated units in all periods before g. Unlike other approaches, this methodology explicitly addresses treatment effect heterogeneity in staggered DiD settings, offering greater robustness and flexibility. While alternative methodologies are of interest, their exploration lies beyond the scope of this study and points to directions for future research.

The methodology proposed by Callaway and Sant'Anna allows for further generalizations in the identification assumptions of causal effects, including: the possibility of allowing for a time-limited anticipatory effect in treated units; the inclusion of units in the control group at a given time that are 'not yet treated' but will be treated in subse-

[16] The standard approach to modelling staggered DiD, essentially based on estimating a two-way fixed effect (TWFE) model, has been widely criticised (Borusyak *et al.*, 2024; Athey and Imbens, 2022; Goodman-Bacon, 2021; de Chaisemartin and D'Haultfoeuille, 2020; Sun and Abraham, 2021). Among these critiques, mostly related to the fact that the TWFE implicitly assumes homogeneous treatment effects across time and units – possibly misspecifying the treatment effect dynamics – one is the so-called 'negative weight problem' (de Chaisemartin and D'Haultfoeuille, 2020; Goodman-Bacon, 2021) which can lead to misleading and hard-to-interpret results especially when interested in quantifying an 'aggregate' treatment effect for the whole time period. Goodman-Bacon (2021) showed that the estimated 'overall' treatment effect coefficient obtained with the TWFE model is a weighted average of the average treatment effects obtained on all possible 2x2 DiD comparisons between different treatment groups and timing, and some of these 2x2 DiD use already-treated units as control units, leading to negative weights. When treatment effects vary over time or across groups, these negative weights can bias the overall treatment effect estimate, sometimes even changing its sign, further complicating its interpretation. Several alternatives to the TWFE approach have been proposed in the literature; for a comprehensive review, see Roth *et al.* (2023).

quent periods; the extension of the parallel trends assumption to the case where it holds conditionally on a specific set of regressors, enabling the use of alternative estimation methods such as outcome regression (Heckman *et al.*, 1997, 1998), inverse probability weighting (Abadie, 2005), and the doubly-robust method (Sant'Anna and Zhao, 2020).[17]

The information richness generated by the Callaway and Sant'Anna's estimation methodology can be summarised in various ways, depending on the research question of interest. In our case, we are primarily interested in evaluating how any innovative effect due to PE manifests over time, starting from the year the firm is involved in the agreement ($t = g$) and without considering the specific calendar year in which the agreement was completed. This approach is similar to that of 'event studies' typical of the staggered DiD literature, in which the temporal dynamics of causal effects on the treated group are evaluated by 'standardising' the time scale of all treatment groups.

It is worth emphasising that, in our study, a firm's likelihood of being involved in a PE deal may be reinforced by its ability to showcase its innovative capabilities to attract PE investors. At the same time, PE investors may themselves be able to identify and invest in firms with higher innovative capabilities, thereby capitalising on innovation processes that are already underway. Both mechanisms could introduce reverse causality, thereby complicating the precise measurement of causal effects. We believe that such a problem is common amongst most of the econometric analyses that attempt to identify causal links (effects) between PE and firm characteristics. Let e be the exposure time to treatment and e' be the minimum number of periods in which a treatment group remained treated ($e \leq e' \leq T - 2$). Treatment event occurs at $e = 0$, subsequent periods ($e = 1, e = 2, \dots$) are positive exposure times (one period after, two periods after, etc.), and the periods before ($e = -1, e = -2, \dots$) are negative exposure times (one period before, two periods before, etc.). The approach of Callaway and Sant'Anna involves determining the treatment effect e time points subsequent (or preceding) to the treatment event, for all groups that remained treated for at least e' periods: $\theta(e; e')$.[18] The 'event-study plot' is the usual tool for visualizing these effects and shows, for a fixed e', the dynamics of $\theta(e; e')$ across all negative ($e = -1, \dots, e = -(T - e' - 2)$) and positive ($e = 0, e = 1, \dots, e = e'$) exposure times.

4.3 Results

We employ the methodology proposed by Callaway and Sant'Anna (2021), where $t = 2010, 2011, \dots, 2019$ and $g = 2011, \dots, 2019$. In what follows, we will interchangeably

[17] For a detailed discussion of the methodology and the assumptions underlying these extensions, which enable the identification of $ATT(g, t)$, we refer readers to the original article.

[18] The authors define $\theta(e; e')$ as the weighted average of all the $ATT(g, g + e)$ corresponding to all treatment groups g that remained treated for at least e' periods ($g \leq T - e'$), with weights proportional to the sample size of each treatment group.

refer to 'treated' firms and those involved in PE agreements, as well as to 'treatment' and 'PE agreements'. Considering the heterogeneity in the distribution of patent applications, both across different firms and within the same firm over different years, it is appropriate to apply a logarithmic transformation to the response variable proxying the innovation strength for firm i in year t: $Y_{it} = \ln(1 + PatentApplications_{it})$. The same transformation has been applied to $GreenApplications_{it}$. The addition of a unitary term is necessary because, in most cases, the number of patent applications filed by a firm in a year is zero. The logarithmic transformation allows the ATT to be interpreted, as a first-order approximation, as the difference between the percentage change in the outcome of treated firms and that of the control group, capturing the variation attributable to the PE agreement.[19]

The employed methodology allows for the formulation of the parallel trend assumption conditioned on some explanatory variables. These are chosen to be the country of origin and the primary business sector. Our hypothesis is that, conditioned on these two characteristics, firms would exhibit a parallel relative trend of evolution in the absence of treatment. In other words, it is plausible to assume that firms operating in the same sector and residing in the same country share a similar reference context, such that they have a comparable patent application trend in the absence of PE.

The estimation of the $ATT(g,t)$s and their subsequent aggregation into the $\theta(e;e')$s have been conducted using the R package `did` developed by Callaway and Sant'Anna.[20] From the estimation sample, all firms that never filed any patent applications over the decade have been excluded, as they are assumed to be unlikely to generate industrial or scientific patents because of the peculiarities of their activities.[21] Therefore, PE would not have any significant impact on these firms in terms of patent generation, and their inclusion in the estimating sample could produce biased results. Several estimates have been carried out by combining the following choices:

- Response variable: number of patent applications filed by a firm in a given year, including both total patents (case 'All Patents') and green patents only (case 'Green Patents');

- Estimation sample (treatment and control groups): it includes only firms that filed

[19] However, Chen and Roth (2024) have pointed out that such a practice should be used with caution, as these changes depend on the unit of measurement of the response variable, unlike a 'true' percentage change. The logarithmic transformation of the response variable also appears more appropriate in our case to explicitly express the 'parallel trends' assumption underlying the DiD methodology. It is in fact reasonable to assume that, given the varied size of the firms in the treatment and control groups, the average number of patent applications filed by the two groups evolves similarly in relative terms – rather than absolute terms – over time.

[20] The package is available for download from CRAN: `https://cran.r-project.org/web/packages/did/index.html`

[21] Summary descriptive statistics for this subset, disaggregated by group (treatment and control), country, and sector, are reported in Appendix B.

a positive number of patent applications (either total or green only, depending on the chosen case) in at least one year of the decade (case 'Patent creators') or in at least five years (case 'Frequent patent creators');

- Treatment group: it consists of firms that have been involved in PE deals (whether VC or not), in VC deals, or in PE deals which are all but VC deals ('No-VC').

Regarding the other estimation options, they are almost identical to the default options implemented in the `R` package.[22] Following the approach suggested by Callaway and Sant'Anna, the $\theta(e; e')$s are further aggregated into an overall measure, $\theta^O(e)$, showing the average effect of being involved in a PE deal in the first e' years after the deal. This measure is the arithmetic mean of all the $\theta(e; e')$s for positive exposure times ($0 \leq e \leq e'$).

We separately deal with the entire universe of patent applications and with the subset of green patents. Countries and/or sectors deemed under-represented in the sample are excluded from the estimation. The number of firms that filed at least one green patent application during the decade is significantly lower than that of firms that filed at least one patent application of any kind; an adequate number of firms in each country and sector is required to empirically support the hypothesis of parallel trends conditioned on these two variables. In the 'All patents' estimation case, no country is excluded, but only firms from sectors C ('Manufacturing'), F ('Construction'), G ('Wholesale and retail trade; repair of motor vehicles and motorcycles'), J ('Information and communication'), M ('Professional, scientific and technical activities') and N ('Administrative and support service activities') are included. In the 'Green patents' estimation case, all Portuguese firms are excluded, and only firms from sectors C ('Manufacturing'), G ('Wholesale and retail trade; repair of motor vehicles and motorcycles') and M ('Professional, scientific and technical activities') are retained.

Figures 2 and 3 present the estimated values of $\theta(e; e')$ (on the y-axis) across different exposure periods e (x-axis) for the 'All patents' and 'Green patents' estimation cases, respectively. Each point corresponds to the single $\theta(e; e')$ point estimate, and the segment represents the 95 per cent confidence interval around that estimate. The colour distinguishes estimates corresponding to post-treatment periods (light blue) and pre-treatment periods (orange). At the top of each graph, the overall measure $\theta^O(e')$ ('Overall ATT') is reported, along with its 95 per cent confidence interval.

[22] No anticipatory effect is assumed in the treatment (i.e. the PE agreement manifests its effects on patent applications only from the year of the agreement onward); the control group has been restricted solely to firms that were never involved in PE deals over the decade; the doubly-robust estimator proposed by Sant'Anna and Zhao (2020) is used for estimating the $ATT(g, t)$s, as it combines two alternative techniques (outcome regression and inverse probability weighting). The confidence intervals around the estimates are constructed using a bootstrap resampling strategy with 1,000 replications, and the chosen confidence level is set at 95%. The aggregation of the $ATT(g, t)$s into $\theta(e; e')$ is carried out by choosing $e' = 3$, which we considered to be a good compromise between the information richness of the resulting 'event-study plots' and the goodness of fit of the aggregated effects.

Empirically, we expect that all $\theta(e; e')$s for $e < 0$ are not significantly different from zero (i.e., the orange intervals should all contain zero). This assumption is based on the idea that, in the years prior to the treatment, the treated group is on average the same as the control group, meaning that any pseudo-effects due to potential treatment do not exist. If this assumption is confirmed by the data, it is reasonable to infer (although it is not a statistical consequence) that the parallel trend hypothesis would hold in the subsequent years in the absence of treatment. For each $e \geq 0$, a treatment effect is statistically present if $\theta(e; e')$ is significantly different from zero (i.e., the corresponding light blue interval does not contain zero). Depending on whether the interval is above or below the dashed line representing zero, the sign of the causal effect is positive or negative. The overall effect $\theta^O(e')$ is statistically significant if its confidence interval does not contain zero.

Regarding the entire universe of patents (Figure 2), a significantly positive relationship emerges for all PE deals (panels a and b), and, to a somewhat greater extent, also for VC deals (panels c and d). Conversely, the no-VC deals (panels e and f) do not show any significant effect, supporting the hypothesis that the truly positive contribution in the PE is given by VC. The positive relationship (where it exists) tends to start from the year in which the agreement is concluded ($e = 0$) and to increase in the following years ($e = 1, 2$). By the third year ($e = 3$), the effect seems to decrease. The lack of significance of pseudo-ATT effects in all years before the agreement conclusion is not entirely clear, except for panel b, where a statistical 'pre-test' proposed by Callaway and Sant'Anna does not reject the null hypothesis of parallel trends between the treated group and the control group. We consider the results from the estimates performed on the subset of 'Frequent patent creators' (panels b, d and f) to be more reliable in terms of statistical significance. These are firms for which there is a positive number of patent applications in at least half of the years in the sample; thus, for each firm, we believe the response variable to be somewhat more reliable.

Growth in patent activity seems to emerge in the calendar year preceding the agreement ($e = -1$), although it is not statistically significant in all cases, and its magnitude is generally much smaller. Nevertheless, it cannot be entirely ruled out that a positive relationship already appears in the year before the agreement is concluded, supporting the hypothesis of a signalling effect by firms that seek to attract PE investors. It is plausible that firms with innovative capabilities try to attract PE investors, and these investors tend to 'ride the wave' by joining the firm and helping it to improve and amplify an innovation process that has already begun.

The overall measures ('Overall ATT') for panels a, b, c and d are significantly positive, supporting the evidence of a rise in patenting activity for firms involved in PE deals and in VC agreements; for those involved in PE deals which are not VC-type (no-VC), the overall measures are not significantly different from zero.

By adopting $\ln(1 + PatentApplications_{it})$ as the response variable on which to assess the effect, the estimated Overall ATT can be interpreted, as a first-order approximation, as the overall difference between the percentage change in innovation output of PE-involved firms and that of the control group, capturing the variation attributable to the PE agreement. This approximation is more accurate the higher a firm' prior innovative capacity was before the PE agreement, that is, if the firm submitted an average number of patent applications well above a few units.[23] Therefore, for a firm involved in PE (Figure 2, panel a), the estimated overall average increase in patenting submissions exceeds that of the control by approximately 19% (with a confidence interval between 13 and 25 percent), rising to a statistically significant superior 43% (32%, 54%) approximate increase if the agreement type is VC (Figure 2, panel c). For a firm characterized by strong patenting activity over the examined decade, this effect is on average – although not statistically significant – higher (22 percent approximately, rising to about 50 percent approximately if the agreement involved is VC – Figure 2, panel b and d respectively).

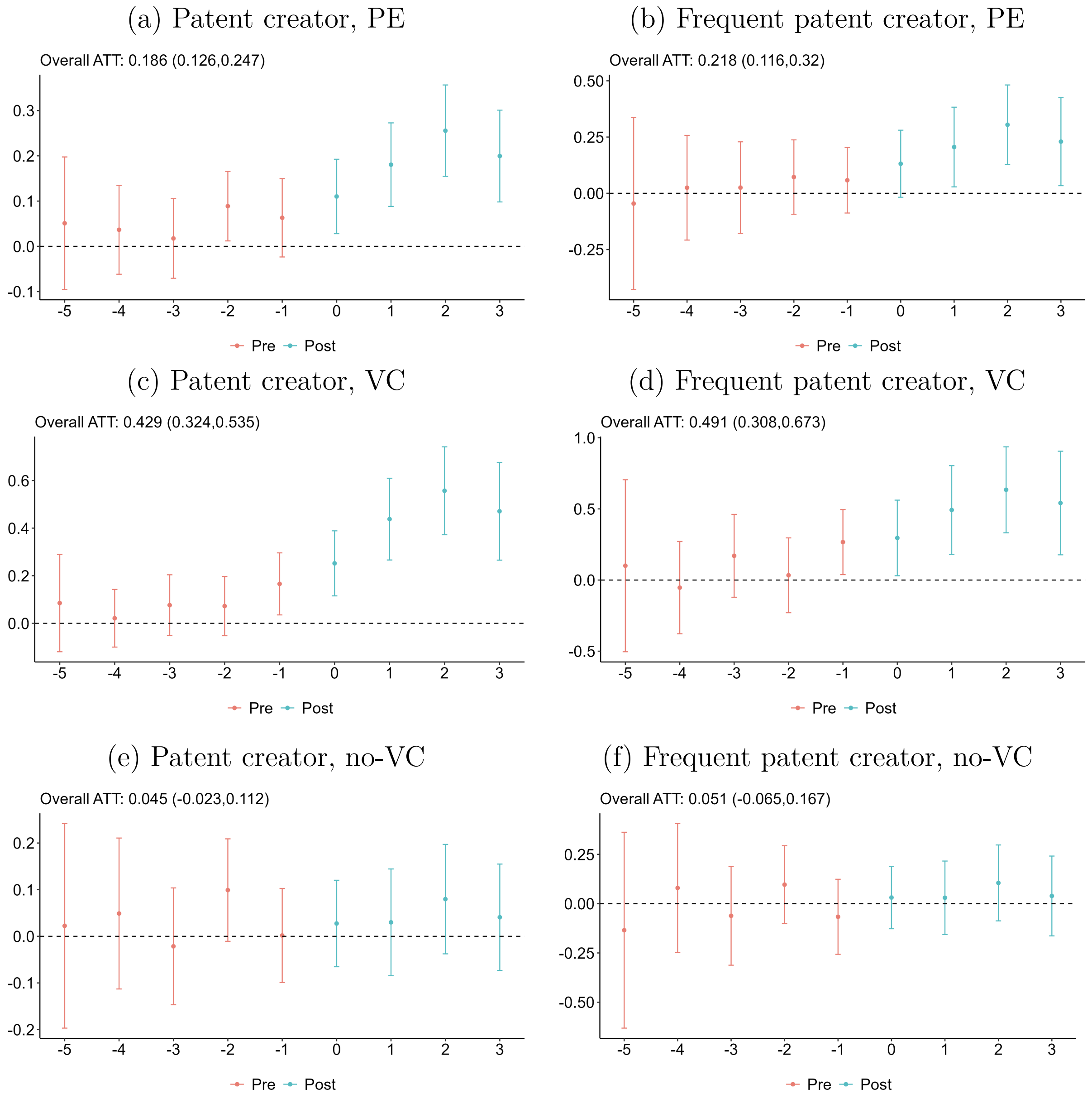
These conclusions do not hold for the 'Green patents' case (Figure 3). Overall, there is little evidence supporting the hypothesis that PE investment produces a positive effect on green innovation. The effects in all years following the conclusion of the agreement do not appear to be significantly different from zero and the overall ATTs are not significant. The only exception relates to VC for 'Patent creators' (panel c). However, as we said before, we believe that this category is less representative than the 'Frequent patent creators' one. Thus, we do not feel confident enough to conclude that such exceptions show the existence of any relationship. These results are consistent with the results of the exploratory analysis in the previous section. The small sample size of the subset of firms involved in green innovation processes, as well as the inherent difficulty in measuring the existence of such processes, make it challenging to detect any positive effect from PE. It is also conceivable that positive effects do exist, but they are too recent, i.e. occurring in the years after 2019, to be detected within our sample.

[23]Notice $\ln(1 + x) - \ln(1 + y) = \ln(x) - \ln(y) + \ln((1 + x^{-1})/(1 + y^{-1}))$ and the third addendum cancels if both $x >> 0$ and $y >> 0$. Given that, $ATT = \mathbb{E}[\ln(1 + Y(1)) - \ln(1 + Y(0)) \mid D = 1] \simeq \mathbb{E}[\ln(Y(1)/Y(0)) - 1 \mid D = 1]$ if, conceptually, both the patenting activity post-deal ($Y(1)$) and pre-deal ($Y(0)$) is greater than some few units. Notice also the effect for treated firms with zero patenting activity is undefined.

Figure 2

Event-study plot for the effect of PE on innovation

All patents

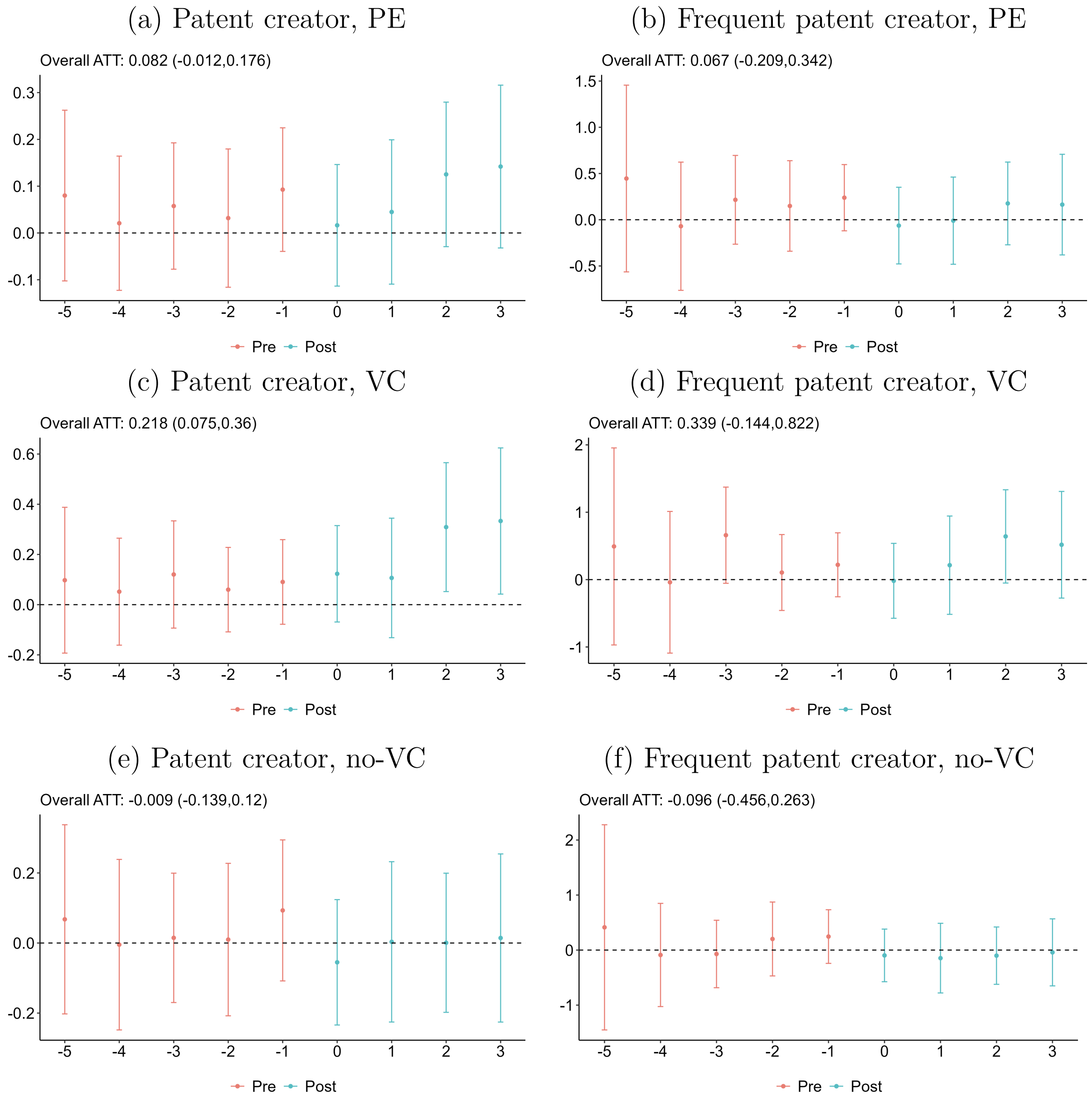


Notes. The values on the x-axis represent the time difference (in years) from the year of the deal, while the values on the y-axis represent the estimated values of $\theta(e; e')$. Segments represent the 95% confidence interval around the estimate; numbers in brackets near the Overall ATT estimates represent the associated 95% confidence interval. Intervals including zero indicate that the associated parameter is not statistically significant at the 5% level.

Figure 3

Event-study plot for the effect of PE on green innovation

Green patents



Notes. See figure 2.

4.4 Comparison with recent empirical studies

As context factors likely play a key role in determining the effect of PE investments on innovation output by target firms, we limit the comparison of our empirical results with recent research on EU countries. First, our results support the idea that VC investments foster innovation output by target firms (Faria and Barbosa, 2014; Bronzini *et al.*, 2020). Second, the impact of PE investment at large is limited, probably depending on a number of factors relating to the characteristics of the PE investor and the deal (Ughetto, 2010). Third, although firms with the highest level of innovation may tend to attract VC investors the most (Pradhan *et al.*, 2017; Colombo *et al.*, 2023), we find evidence of a positive impact on innovation of the VC deals on the entire sample of target firms ('patent creator'), not only on the subset of the most innovative target firms ('frequent patent creator'). This is somehow in contrast with evidence from previous research that only detects directional causality from innovation to VC investment (Geronikolaou and Papachristou, 2012). Fourth, our results support the view that the impact of PE investments on green innovation is still scarce, probably due to a set of factors limiting the upside potential of green investments (Van den Heuvel and Popp, 2023).

5 Conclusions

The findings of this study support the hypothesis that PE investments are positively related to the innovation by EU firms, as shown by the increase in patent activity, particularly in the years following the agreement. The positive effect is driven by VC investments, which tend to support firms with established innovation potential. Conversely, other forms of PE investments show no significant correlation, although they can contribute to a firm's development through different channels.

However, our results also highlight potential signalling effects prior to PE agreements: firms with stronger patent activity tend to attract a larger share of PE funding. This finding suggests that PE investors not only foster innovation after investment but are also adept at identifying and amplifying existing innovation trajectories. Furthermore, highly innovative firms may be able to implement strategies that effectively attract private equity investors. Therefore, a reverse causality mechanism cannot be entirely ruled out and we cannot conclude that PE investments unambiguously create innovation from scratch. For green innovation the evidence is inconclusive, suggesting that PE investments, whether VC-type or not, may not fully align with the unique needs of environmentally-enhancing technologies. Factors such as the high risk and longer time horizons associated with green technologies, combined with the lack of stable policy support in some contexts, may have limited the ability of PE to drive significant advancements in this area. Given the massive deployment of new technologies required to achieve carbon neutrality, the study of the interaction between private capital investment and green innovation is a much-needed area for further research and policy action. Patient PE investors could be the best suited to (i) finance new high-risk technological opportunities and (ii) navigate a context in which investors in public markets divest brown firms, instead of driving them towards a sustainable path (World Economic Forum, 2022).

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Appendix

A Data retrieving and assembling from the Orbis ecosystem database

As described in Section 3, the data used in this study were retrieved from Moody's Orbis ecosystem.

For the identification of firms, these were selected from the 'Orbis' database (see Section 3.1) among all companies that, at the time of the query: were active, had their registered office in one of the eight euro area countries considered, operated outside the macro-sectors 'K – Financial and insurance activities' and 'L – Real estate activities' of the NACE Rev. 2 classification, and were not classified as 'micro' according to the EU size classification.[24] The rationale behind these choices is detailed in the text. The selected fields, in addition to the primary key ('BvD ID number', which enables linkage across databases within the Orbis ecosystem), include the main firm-level characteristics (name, country, primary industry, size).

For the identification of deals, these were selected from the 'Orbis M&A' database (see Section 3.3) among all recorded M&A transactions that, at the time of the query: were completed between January 1st, 2010 and December 31st, 2019, included at least one financing type classification among 'Private Equity' or 'Venture Capital', and in which at least one of the target firms belong to the country and industry sector of interest. The selected fields include, in addition to the deal identifier, the identifier ('BvD ID number') and name of the target firm(s), acquiror(s), and vendor(s) involved in the deal, the completion date, the financing types, as well as additional deal-level information not used in this study. Given the selection criteria, at least one financing type for each deal is always either 'Private Equity' or 'Venture Capital'; therefore, deals financed with 'Venture Capital' have been classified as 'VC', while those financed with 'Private Equity' as 'no-VC'. No deals feature both financing types.

For the identification of patents, these were selected from the 'Orbis Intellectual Property' database (see Section 3.2) among those with a filing date between January 1st, 2010 and December 31st, 2019, and whose applicant belongs to the set of firms extracted from the 'Orbis' database. The selected fields include, in addition to the patent identifier and the applicant firm identifier ('BvD ID number'), the filing date and the IPC and CPC classifications used in the 'green tagging' procedure described in the paper. Once each patent was classified as green or non-green, the data were aggregated so that, for each (firm, year) pair, the number of patent applications filed in that year (both green and non-green) and the corresponding number of only-green patent applications were

[24] In the absence of dimensional variables (employees, balance sheet size) for some jurisdictions, we also rely on the proprietary Orbis size classification.

available.

The three extracted datasets were then subject to further data cleaning procedures, including the reapplication of the selection filters used at the download stage and the removal of missing keys and inconsistent records. Subsequently, a panel dataset was constructed by merging the three datasets. The presence of the 'BvD ID number' field in all three datasets (being the firm identifier in the 'Orbis' extract, the target firm identifier in the 'Orbis M&A' extract, and the applicant firm identifier in the 'Orbis Intellectual Property' extract) and of the 'Year' field in the two longitudinal datasets (being the deal completion year in 'Orbis M&A' and patent filing year in 'Orbis Intellectual Property') enabled the construction of the panel dataset by associating each (BvD ID number, Year) pair with the corresponding record through a standard left-join procedure on the relevant primary keys. The assembly of the panel dataset required handling the specific case of firms involved as targets in multiple deals over the decade considered: in such cases, only the earliest deal was retained, under the assumption that it represents the 'dominant' transaction marking the most significant entry of the investor.

The resulting panel dataset includes the following columns:

- BvD ID number (primary key): firm identifier
- Year (primary key): year identifier
- Firm-level characteristics (name, country, industry, size), constant over time
- Patent activity variables (number of (green) patent applications filed in a given year and market share of (green) patent applications filed in that year)
- Variables related to involvement as a target in a deal (financing type, deal value, deal identifier), which are all NA for firms not belonging to the treatment group

Descriptive statistics for this dataset are extensively reported in Section 3.4, with the aim of giving a representative picture of patenting and PE activity in the euro area, discriminating both against sector and country.

B Data description of the subset of firms used for the staggered DiD analysis

As already highlighted in the text, the econometric analyses presented in Section 4 were restricted to the subset of firms that, over the decade under consideration, had filed: (i) at least one patent application in at least one year ('Patent creators'); (ii) at least one patent application in at least five years ('Frequent patent creators'). The restriction was applied considering both any type of patent (green or non-green) and, separately, only 'green' patents. The rationale for this choice has been discussed in the main text. Furthermore, following these restrictions, only firms belonging to adequately represented countries and sectors were retained. The combination of these restrictions led to a substantial reduction in the sample size of the dataset under analysis.

The following tables report the sample sizes of the treatment and control groups used for the estimates presented in Figures 2 and 3, disaggregated by sector and country. For the group of firms targeted by a deal completed in 2010 ($g = 2010$), being the first treatment group and coinciding with the first observed time period ($t = 2010$), it was not possible to estimate any $ATT(g, t)$; therefore, this treatment group was excluded from the analysis.

Table B1 reports the sample sizes underlying the estimates shown in figure 2, panel c and d. Table B2 refers to figure 2, panel e and f. Table B3 refers to figure 3, panel c and d. Table B4 refers to figure 3, panel e and f. In each table, the number of firms classified as ‘Patent creators’ is reported, with the number of ‘Frequent patent creators’ shown in parentheses. The sample sizes referring to the PE group (VC + No-VC) used to produce the estimates in figure 2, panel a and b (figure 3, panel a and b respectively) are not reported, as they can be directly inferred by summing the figures reported in tables B1 and B2 (tables B3 and B4, respectively).

Table B1

VC: control and treatment group
for staggered DiD analysis on innovation

Patent creators and, in parentheses, Frequent patent creators

	Control group	Treatment group (by year of treatment)											Total
		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total	
Total													
	47,664	61	63	51	63	66	101	82	91	85	67	730	48,394
	(11,003)	(40)	(41)	(33)	(33)	(29)	(39)	(23)	(16)	(21)	(3)	(278)	(11,281)
Country													
Austria	1,794	2	1	1	4	1	3	3	2	2	0	19	1,813
	(545)	(0)	(1)	(1)	(2)	(1)	(0)	(1)	(1)	(0)	(0)	(7)	(552)
Belgium	1,609	2	1	2	8	3	8	4	7	10	12	57	1,666
	(352)	(0)	(1)	(2)	(7)	(1)	(4)	(1)	(0)	(3)	(0)	(19)	(371)
France	6,145	24	22	26	18	29	42	29	37	29	22	278	6,423
	(1,588)	(17)	(13)	(20)	(11)	(11)	(15)	(10)	(9)	(5)	(2)	(113)	(1,701)
Germany	19,225	22	23	17	21	22	23	18	26	25	12	209	19,434
	(5,052)	(16)	(16)	(8)	(9)	(12)	(12)	(4)	(5)	(6)	(0)	(88)	(5,140)
Italy	11,314	3	1	1	4	2	7	10	4	8	8	48	11,362
	(2,229)	(2)	(1)	(0)	(2)	(1)	(2)	(5)	(1)	(4)	(1)	(19)	(2,248)
Netherlands	2,529	6	7	1	3	5	7	5	5	7	9	55	2,584
	(561)	(4)	(4)	(0)	(1)	(3)	(3)	(2)	(0)	(2)	(0)	(19)	(580)
Portugal	571	0	0	0	0	3	0	1	1	1	1	7	578
	(59)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(1)	(0)	(1)	(60)
Spain	4,477	2	8	3	5	1	11	12	9	3	3	57	4,534
	(617)	(1)	(5)	(2)	(1)	(0)	(3)	(0)	(0)	(0)	(0)	(12)	(629)
Sector													
C	28,730	15	19	14	17	15	23	24	19	20	12	178	28,908
	(7,735)	(11)	(12)	(11)	(10)	(9)	(8)	(10)	(6)	(8)	(1)	(86)	(7,821)
F	2,196	1	1	0	0	0	1	0	0	1	0	4	2,200
	(194)	(0)	(1)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(1)	(195)
G	7,686	5	6	5	8	4	10	3	7	5	1	54	7,740
	(1,141)	(3)	(5)	(3)	(3)	(1)	(5)	(0)	(0)	(3)	(0)	(23)	(1,164)
J	1,897	10	10	10	17	23	26	15	27	21	15	174	2,071
	(245)	(3)	(0)	(2)	(5)	(6)	(6)	(0)	(1)	(0)	(0)	(23)	(268)
M	6,073	28	27	20	20	24	41	40	38	37	37	312	6,385
	(1,534)	(22)	(23)	(17)	(15)	(13)	(20)	(13)	(9)	(9)	(2)	(143)	(1,677)
N	1,082	2	0	2	1	0	0	0	0	1	2	8	1,090
	(154)	(1)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(1)	(0)	(2)	(156)

Source: Orbis; own elaborations.

Notes. The sectoral classification is based on the NACE Rev. 2 classification.
C=Manufacturing; F=Construction; G=Wholesale and retail trade; J=Information and communication; M=Professional, scientific and technical activities; N=Administrative and support service activities.

Table B2

No-VC: control and treatment group for staggered DiD analysis on innovation

Patent creators and, in parentheses, Frequent patent creators

	Control group	Treatment group (by year of treatment)											Total
		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total	
Total													
	47,664 (11,003)	116 (56)	129 (60)	129 (64)	96 (46)	149 (63)	130 (54)	96 (38)	116 (44)	116 (42)	126 (45)	1,203 (512)	48,867 (11,515)
Country													
Austria	1,794 (545)	3 (1)	2 (2)	1 (0)	3 (2)	1 (0)	3 (3)	7 (6)	0 (0)	2 (1)	2 (1)	24 (16)	1,818 (561)
Belgium	1,609 (352)	7 (3)	8 (4)	5 (1)	8 (4)	9 (5)	9 (4)	11 (4)	8 (3)	7 (1)	6 (3)	78 (32)	1,687 (384)
France	6,145 (1,588)	53 (31)	43 (21)	56 (25)	33 (15)	62 (28)	49 (17)	26 (4)	29 (9)	31 (11)	28 (6)	410 (167)	6,555 (1,755)
Germany	19,225 (5,052)	25 (14)	32 (11)	26 (15)	21 (10)	25 (14)	23 (11)	20 (6)	31 (12)	22 (10)	30 (10)	255 (113)	19,480 (5,165)
Italy	11,314 (2,229)	15 (4)	21 (13)	15 (9)	13 (7)	19 (9)	19 (10)	18 (12)	21 (12)	29 (14)	36 (14)	206 (104)	11,520 (2,333)
Netherlands	2,529 (561)	6 (1)	11 (5)	12 (7)	5 (2)	18 (3)	8 (3)	2 (2)	9 (2)	10 (1)	6 (3)	87 (29)	2,616 (590)
Portugal	571 (59)	2 (0)	1 (0)	0 (0)	3 (0)	1 (0)	6 (1)	1 (0)	1 (1)	1 (0)	0 (0)	16 (2)	587 (61)
Spain	4,477 (617)	5 (2)	11 (4)	14 (7)	10 (6)	14 (4)	13 (5)	11 (4)	17 (5)	14 (4)	18 (8)	127 (49)	4,604 (666)
Sector													
C	28,730 (7,735)	66 (36)	74 (43)	78 (42)	59 (32)	84 (42)	78 (35)	57 (23)	62 (28)	67 (31)	77 (31)	702 (343)	29,432 (8,078)
F	2,196 (194)	2 (0)	4 (0)	1 (0)	1 (0)	3 (1)	0 (0)	1 (0)	0 (0)	2 (0)	3 (1)	17 (2)	2,213 (196)
G	7,686 (1,141)	17 (7)	17 (5)	17 (7)	11 (5)	21 (6)	17 (5)	10 (4)	8 (5)	11 (3)	12 (3)	141 (50)	7,827 (1,191)
J	1,897 (245)	11 (4)	10 (4)	13 (4)	11 (2)	12 (2)	19 (4)	12 (2)	21 (4)	10 (0)	15 (3)	134 (29)	2,031 (274)
M	6,073 (1,534)	20 (9)	18 (8)	18 (10)	10 (5)	28 (12)	16 (10)	16 (9)	19 (5)	25 (7)	19 (7)	189 (82)	6,262 (1,616)
N	1,082 (154)	0 (0)	6 (0)	2 (1)	4 (2)	1 (0)	0 (0)	0 (0)	6 (2)	1 (1)	0 (0)	20 (6)	1,102 (160)

Source: Orbis; own elaborations.
Notes. See table B1.

Table B3

VC: control and treatment group numerosity for staggered DiD analysis on green innovation

Patent creators and, in parentheses, Frequent patent creators

	Control group	Treatment group (by year of treatment)											Total
		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total	
Total													
	9,760 (1,684)	25 (8)	29 (5)	16 (5)	20 (7)	18 (5)	30 (5)	22 (3)	21 (0)	20 (3)	14 (0)	215 (41)	9,975 (1,725)
Country													
Austria	478 (111)	0 (0)	1 (1)	0 (0)	1 (0)	0 (0)	1 (0)	1 (0)	0 (0)	0 (0)	0 (0)	4 (1)	482 (112)
Belgium	377 (71)	0 (0)	1 (0)	2 (1)	3 (1)	2 (0)	2 (0)	1 (0)	1 (0)	4 (0)	1 (0)	17 (2)	394 (73)
France	1,407 (300)	8 (2)	10 (2)	10 (3)	9 (2)	6 (1)	13 (2)	9 (2)	11 (0)	4 (2)	6 (0)	86 (16)	1,493 (316)
Germany	4,329 (844)	10 (5)	8 (2)	2 (1)	5 (3)	7 (4)	7 (3)	4 (1)	6 (0)	6 (1)	3 (0)	58 (20)	4,387 (864)
Italy	1,837 (180)	3 (0)	1 (0)	0 (0)	1 (0)	0 (0)	3 (0)	3 (0)	1 (0)	2 (0)	2 (0)	16 (0)	1,853 (180)
Netherlands	578 (103)	3 (1)	3 (0)	0 (0)	0 (0)	3 (0)	2 (0)	3 (0)	1 (0)	4 (0)	2 (0)	21 (1)	599 (104)
Spain	754 (75)	1 (0)	5 (0)	2 (0)	1 (1)	0 (0)	2 (0)	1 (0)	1 (0)	0 (0)	0 (0)	13 (1)	767 (76)
Sector													
C	6,415 (1,191)	9 (3)	10 (1)	4 (2)	7 (2)	10 (1)	8 (0)	7 (0)	6 (0)	4 (0)	3 (0)	68 (9)	6,483 (1,200)
G	1,323 (118)	2 (0)	1 (1)	1 (0)	3 (1)	0 (0)	5 (1)	1 (0)	2 (0)	2 (1)	0 (0)	17 (4)	1,340 (122)
M	2,022 (375)	14 (5)	18 (3)	11 (3)	10 (4)	8 (4)	17 (4)	14 (3)	13 (0)	14 (2)	11 (0)	130 (28)	2,152 (403)

Source: Orbis; own elaborations.
Notes. The sectoral classification is based on the NACE Rev. 2 classification.
C=Manufacturing; G=Wholesale and retail trade; M=Professional, scientific and technical activities.

Table B4

No-VC: control and treatment group numerosity for staggered DiD analysis on green innovation

Patent creators and, in parentheses, Frequent patent creators

	Control group	Treatment group (by year of treatment)											Total
		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total	
Total													
	9,760 (1,684)	39 (9)	36 (12)	41 (10)	25 (7)	43 (10)	29 (6)	28 (4)	25 (6)	27 (5)	32 (6)	325 (75)	10,085 (1,759)
Country													
Austria	478 (111)	2 (0)	1 (0)	0 (0)	2 (1)	0 (0)	3 (0)	3 (1)	0 (0)	0 (0)	1 (0)	12 (2)	490 (113)
Belgium	377 (71)	3 (1)	2 (0)	1 (0)	2 (1)	2 (0)	1 (1)	3 (1)	1 (0)	0 (0)	0 (0)	15 (4)	392 (75)
France	1,407 (300)	16 (4)	10 (3)	14 (2)	11 (4)	22 (9)	9 (3)	7 (1)	3 (1)	8 (2)	6 (2)	106 (31)	1,513 (331)
Germany	4,329 (844)	13 (3)	11 (5)	12 (3)	6 (1)	6 (1)	8 (1)	4 (0)	10 (3)	9 (3)	13 (3)	92 (23)	4,421 (867)
Italy	1,837 (180)	4 (1)	8 (3)	4 (0)	2 (0)	5 (0)	5 (0)	4 (1)	4 (1)	4 (0)	7 (1)	47 (7)	1,884 (187)
Netherlands	578 (103)	0 (0)	3 (1)	6 (3)	1 (0)	4 (0)	2 (1)	0 (0)	2 (0)	2 (0)	0 (0)	20 (5)	598 (108)
Spain	754 (75)	1 (0)	1 (0)	4 (2)	1 (0)	4 (0)	1 (0)	7 (0)	5 (1)	4 (0)	5 (0)	33 (3)	787 (78)
Sector													
C	6,415 (1,191)	28 (8)	26 (9)	26 (6)	18 (5)	29 (9)	20 (4)	18 (2)	16 (4)	14 (1)	20 (3)	215 (51)	6,630 (1,242)
G	1,323 (118)	3 (0)	3 (2)	5 (2)	3 (1)	4 (0)	3 (0)	5 (0)	1 (0)	3 (1)	4 (1)	34 (7)	1,357 (125)
M	2,022 (375)	8 (1)	7 (1)	10 (2)	4 (1)	10 (1)	6 (2)	5 (2)	8 (2)	10 (3)	8 (2)	76 (17)	2,098 (392)

Source: Orbis; own elaborations.
Notes. See table B3.

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