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University–industry interaction and firms' innovation performance: new evidence from the biopharmaceutical industry

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Abstract
This study examines the impact of university-industry (U-I) interaction on firms' innovation performance in the biopharmaceutical industry, focusing on understanding the temporal relationship between co-publishing and innovation. Using a sample of Italian biopharmaceutical firms from 2000 to 2010, we explore whether collaborative research, specifically co-publishing between public and private research entities, influences firms' likelihood of innovation and the intensity of their innovation activities. Our investigation sheds light on the temporal aspects of the knowledge generation process and its implications for firms' innovation endeavours. It reveals an "anticipatory effect" of co-publishing on innovation outcomes. Our findings, corroborated by a set of robustness checks, detect that the influence of collaboration on innovation activities precedes the appearance of a joint publication, ruling out the hypothesis of "defensive publication" as a complementary part of a firm's overall IP protection strategy pursued by biopharmaceutical firms.

Keywords University–industry interaction · Co-publishing · Innovation activity · Biopharmaceutical industry

JEL Classification L20 · O31 · O32 · O33

1 Introduction

This study examines the impact of university-industry (U-I) interaction on the innovation performance of firms in the biopharmaceutical industry, with a particular focus on understanding the temporal relationship between co-publishing and innovation. The significance of U-I interaction in driving various aspects of firms' performance has been extensively

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explored in economic literature over the past two decades, yielding substantial and multifaceted empirical evidence. Notably, industry-science links have been found to enhance firms' Research and Development (R&D) productivity (Henderson et al., 1998) since collaborations between public research institutions and the private sector generate knowledge spillovers that are crucial for driving innovation (Audia et al., 2006; Mueller, 2006; Owen-Smith & Powell, 2004).

Given the biopharmaceutical industry's heavy reliance on successful research for growth and profitability, it serves as an ideal setting to investigate U-I interaction due to its imperative need to acquire external knowledge and leverage on public spillovers. In fact, biotech and pharmaceutical firms extensively engage with universities and public research centres (Calvert & Patel, 2003; Gittelman & Kogut, 2003) as they strive to efficiently capture new ideas originally developed in university laboratories (Cohen et al., 2002). The discovery and development of new drugs in the life sciences require considerable resources (human, physical, and financial), knowledge integration in particular fields, such as biotechnology and biochemical research (Brusoni et al., 2005), and rigorous interactions between basic and applied research. Therefore, biopharma, more than any other industry, must be used as a system of linkages among different actors (big pharmaceutical firms, small biotech firms, chemical firms, universities, public research centres, national health systems, policymakers, and financial institutions).

This study contributes to existing literature on the role of U–I interaction in firms' innovation behaviour by investigating whether and how firms can benefit from positive knowledge spillovers resulting from collaborations with academia. Precisely, this study investigates whether companies tend to increase their likelihood of patent ownership and/or ramp up innovation activities when engaging in co-publication collaborations with public research institutions. It significantly enhances existing literature by elucidating the role of timing in the relationship between collaboration and innovation, drawing upon data pertaining to patents and co-publications. We investigate the presence of an "anticipatory effect" that, to the best of our knowledge, has never been accounted for in previous literature. Indeed, co-publications are the expression of a scientific collaboration that can be preceded by its effects on innovation activity, as a certain time lag occurs between the joint research activity and the publication in journals, as indexed in the Web of Science. We thus posit that the occurrence of collaborations, as well as their influence on innovation activity, precedes the appearance of a joint publication. A published co-authored work can be located downstream in the knowledge generation process, as private companies will not allow publishing in scientific journals any information about an invention/technology before filing the patent application, since it might compromise the grant allocation. Our hypothesis also finds support in Sternitzke (2010), who shows that the stream of papers following the basic patent and published by the same biopharmaceutical firm is primarily clinical, thus following patent filing and clinical trials. The literature suggests that firms may also adopt a 'defensive publication' strategy. This involves initially disclosing their research results through publications to achieve several objectives: prolonging patent races, diminishing anticipated patent value, expanding patent scope, and thwarting the privatization of inventions (Rotolo et al., 2022). Our study enhances understanding by empirically dissecting the timing aspect neglected in existing literature. We draw conclusions on the temporal correlation between academic publishing and patenting, thereby contributing valuable insights into the IP protection strategies of biopharmaceutical firms. These insights have implications for policy formulation.

To fulfil our research aims, we construct a unique dataset based on the data of Lotti and Marin (2013), merged with data on co-publishing from Giunta et al. (2016). We obtain a sample of Italian firms during a long study period (2000–2010) that includes firms from the chemical, biotech, and pharmaceutical industries. Thus, we enrich the existing empirical evidence by working with data that combine a rich set of information: (i) the wider biopharma industry (publicly traded and private firms from the chemical, biotech, and pharmaceutical industries); (ii) collaborations (co-authorship) with any kind of scientist from the public sector; (iii) patent data for measuring innovation output; and iv) co-authored articles as an objective knowledge transfer variable that can capture individual collaborations (Almeida et al., 2011) while escaping the 'noise of self-evaluation' of survey-based measures. Unlike firms in other industries, pharmaceutical companies publish extensively (EU Commission, 2003; Hicks, 1995; Koenig, 1983; Leten et al., 2010), as their studies serve as tickets for scientific networks (Cockburn & Henderson, 1998; Hicks, 1995). For this industry, collaborative publications represent more than two-thirds of all scientific publications (Calvert & Patel, 2003; Gittelman & Kogut, 2003), therefore co-publishing is a particularly appropriate proxy for U–I interactions in the biopharma industry.

The combination of these four features characterising our data allows us to obtain a systematic perspective on the role of university-industry (U-I) interaction in a firm's innovation performance and its timing. This is particularly relevant as existing empirical evidence is often concentrated on certain types of firms or industries (such as publicly traded biotech companies, small to medium enterprises [SMEs], or young firms), specific categories of scientists (such as collaborations with 'star scientists'), and/or survey-based measures of innovation and U-I interaction.

Our main findings confirm and extend previous empirical evidence on how knowledge spillovers from academia are beneficial to firms as they increase either firms' probability of owning a patent (industry extensive margin) or the intensity of their innovation activities (industry intensive margin). More importantly, they unveil, for the first time, clear evidence of an "anticipatory effect" of co-publishing on firm's innovation, ruling out the hypothesis of 'defensive publication' as a complementary part of biopharma firms' overall IP protection strategy.

The remainder of this paper is organised as follows. Section 2 reviews the most relevant literature and sets out our research hypotheses. Section 3 describes the model's variables and the empirical strategy, and Sect. 4 explores the results. Section 5 contains robustness analyses, while Sect. 6 provides a final discussion and conclusions.

2 Literature and research hypotheses

The relationship between scientific publishing and patenting has been a central theme in the economics literature, given their pivotal roles in fostering and documenting innovation, thereby enhancing the contribution of scientific research to technological advancement. Within this broad topic, we can identify two primary streams of inquiry: the economics of science literature and the innovation literature. While both address closely interrelated and overlapping issues, their analytical focus significantly differs.

The economics of science primarily centers on individual academic scientists, in particular their productivity, incentives, and contributions to knowledge generation. This stream of literature often investigates scientists' dual productivity in terms of both publishing and patenting, emphasizing the potential tensions or synergies between these activities. A primary concern is the possibility that patenting may negatively affect academic research output, potentially leading to "detrimental consequences on the pace of scientific and technological progress" (Breschi et al., 2008:91). This concern stems from the hypothesized substitution effect: academic scientists dedicating time to patenting may have less time to publish or may limit their publications to less prestigious journals to protect intellectual property.

Despite these theoretical concerns, empirical evidence largely contradicts the substitution effect hypothesis. Studies such as those by Klitkou and Gulbrandsen (2010) show no consistent support for the notion that patenting undermines academic publishing. On the contrary, several studies (Blumenthal et al., 1996; Breschi et al., 2008; Calderini & Franzoni, 2004; Calderini et al., 2007; Godin, 1998; Grimm & Jaenicke, 2015; Stephan et al., 2007; Van Looy et al., 2006) suggest a complementary relationship, wherein patenting and publishing mutually reinforce each other. Even concerns about delays in publication to accommodate patent filings appear to be overstated; as Breschi et al., (2008: 92) state, "any negative impact is likely to be only temporary, with no persistent change in the overall publication trend of a scientist."

Shifting to a related but distinct focus, the innovation literature centers on firms and their innovation performance. This stream is particularly relevant for understanding how firms act as intermediaries between academic research and market applications, leveraging scientific publications to inform patentable technologies. Our study speaks to this stream of literature, focusing on the issue of U-I collaboration and firms' innovative performance, tackled from multiple perspectives and in various settings, providing extensive and multifaceted evidence that differs by the type of data, type of proxy for collaboration and innovation, target industrial sectors, field of research, and the role of specific types of scholars. A first large bunch of contributions employs survey data, mainly from the Community Innovation Survey (CIS) or ad hoc surveys (e.g., Apa et al., 2020; Aschhoff & Schmidt, 2008; Bragoli et al., 2022; Carboni & Medda, 2021; De Marchi, 2012; Fritsch & Franke, 2004; García-Vega & Vicente-Chirivella, 2020; Johnston, 2022; Lööf & Broström, 2008; Mansfield, 1991, 1995, 1998; McCann & Simonen, 2005; Protogerou et al., 2017). Empirical evidence has been provided for firms in different countries, and results are mixed. By and large, this literature suggests the existence of a positive impact of collaboration on innovation. Since the early contributions by Mansfield (1991, 1995, 1998), firms' relationships with universities appear to positively influence firms' innovation output. Although Fritsch and Franke (2004) find that R&D cooperation plays only a minor role as a *medium* for knowledge spillovers, McCann and Simonen (2005) highlight how innovation is positively related to the firm having intense face-to-face relations with other firms and organisations since they facilitate knowledge spillovers and knowledge exchanges. Aschhoff and Schmidt (2008) show that R&D cooperation has a positive effect on the success of process innovations but no significant effect on sales of product imitations and on sales of market novelties. Such positive effects of R&D cooperation on innovation have been confirmed for large manufacturing firms (Lööf & Broström, 2008), for SMEs and young firms (Apa et al., 2020; Protogerou et al., 2017), and over the whole business cycle (García-Vega & Vicente-Chirivella, 2020). Nevertheless, Carboni and Medda (2021) show how external R&D enhances innovation outcomes (product) until a certain threshold beyond which firms face over-outsourcing. Caloghirou et al. (2021) find that U-I R&D collaborations are important in shaping firm innovation towards a form of an inverted U and that firms with low levels of knowledge stocks benefit more in terms of innovation from the development of knowledge flows with universities. Very recently, Bragoli et al., (2022: page 21) find that "cooperation with universities does not encourage additional technological innovation, whereas it increases the likelihood of firms adopting a joint innovation strategy, which encompasses both technological and organisational improvements". In such analyses, collaboration variables display a few peculiarities. First, they are self-reported, thus subject to self-evaluation noise; second, they hardly capture individual-level collaborative activities since they refer to collaborations that are likely to be the result of formal arrangements or joint projects; last, but not least, the panel horizon rarely goes beyond a couple of years (e.g., Lööf & Broström, 2008; Caloghirou et al., 2021; Bragoli et al., 2022), when not cross-sectional (Carboni & Medda, 2021).

A second significant array of studies relies on secondary data sources and objective individual-level measures of U-I interaction such as co-publishing (Almeida et al., 2011; Cockburn & Henderson, 1998; McKelvey & Rake, 2016). This literature frequently focuses on very specific sectors or research fields within an industry [e.g., publicly traded, stand-alone biotechnology firms as in Almeida et al. (2011); cancer research as in McKelvey and Rake (2016)] and it has recognised several reasons why U-I collaboration in scientific publications can, in general, facilitate a firm's innovation activity, particularly in science-based industries. First, it provides access to complementary assets necessary for innovation (e.g., basic research, university hospitals). A second aspect concerns access to external knowledge (Rotolo et al., 2022). These engagements involve participating in the collaborative creation of knowledge alongside researchers from outside the company. Such partnerships offer valuable learning experiences for the firm's researchers, helping them to remain at the cutting edge of their field (Kinney et al., 2004). They also grant early exposure to innovative findings (Stern, 2004) and technologies that could be essential for new product development (Hayter & Link, 2018). Importantly, these collaborations are less restrictive compared to other types of inter-organizational relationships like technological alliances (Almeida et al., 2011). Another relevant issue has to do with the sharing of risk associated with R&D activities among participating partners (Faems et al., 2005; McKelvey & Rake, 2016; Soh & Subramanian, 2014).

In most cases, the assessment of how academic knowledge influences a company's innovation performance relies on widely used metrics such as patent counts or innovative output (Lööf & Broström, 2008). On the other hand, when it comes to approximating university-industry collaborations, empirical studies employ various indicators. These indicators encompass a variety of interaction modes such as collaborative projects, joint patenting endeavours involving university researchers, the emergence of academic spin-off companies, and co-authorship of articles involving both university and industry scientists (Link et al., 2007; Lööf & Broström, 2008).

Cockburn and Henderson (1998) first find an effect of the fraction of co-authorships with universities on the log number of patents (they could only rely on 82 observations relative to a sample of 10 firms). Almeida et al. (2011), using counts of patents to measure innovation output on a sample of 115 US firms and 34 European firms over the time horizon 1990-2003, isolate and highlight the role of individual-level collaborative activity in enhancing firm innovation. Whereas McKelvey and Rake (2016) use the discovery of new molecular entities (NME), which are rather infrequent, to document the positive role of co-authorship in cancer research. Recently, Leten et al. (2022) use a 21-year panel dataset (1995-2015) on patent and publication activity of the largest 50 pharmaceutical firms in the world by R&D expenditures. They find that the relationship between basic research and innovation performance is notably influenced, albeit only partially, by both the direct contribution of internal basic research to innovation and the utilization of external basic research in technology development. The absorptive capacity mechanism, particularly in leveraging external basic research, carries greater weight. Therefore, basic research increasingly becomes a direct input into innovation processes.[1]

A different, parallel, strand of literature looks at patent citations as an outcome variable, somehow testing the effect of the U-I interactions (through co-publishing, co-patenting, or the presence of academic 'star' scientists in the collaboration) on the technological importance of patents (among others, Baba et al., 2009; Colen et al., 2022; Messeni Petruzzelli & Murgia, 2020; Zucker & Darby, 2001; Zucker et al., 1998, 2002).

2.1 U-I collaboration and firm's innovation intensive and extensive margin

The literature has largely documented that biopharmaceutical companies publish extensively to be part of the research community, and papers serve as tickets to scientific networks (Cockburn & Henderson, 1998; EU Commission, 2003, pp. 310–311; Hicks, 1995; Koenig, 1983). Thus, publication activity constitutes a particularly relevant output-oriented complement to input-oriented measures of R&D investments in measuring firms' innovation efforts. Furthermore, for such an industry, the share of collaborative publication represents about 70% of total scientific publications (Calvert & Patel, 2003; Gittelman & Kogut, 2003). According to Cockburn and Henderson (1998), co-authorship is often the result of joint research, which represents the most effective opportunity for the exchange of knowledge. Thus, through this channel of knowledge transfer, both explicit and tacit knowledge (Polanyi, 1966) are intentionally and/or unintentionally transferred (Hicks, 1995; Karnani, 2013). Conversely, citations have always been seen more as the exchange of codified knowledge. Furthermore, citations can be done at a distance, whereas co-authorship typically requires face-to-face interaction, extensive discussions, debate, exchange of ideas, and joint problem-solving. Indeed, each drug is accompanied by, on average, about 19 journal publications and 23 additional patents (Sternitzke, 2010).

Therefore, controlling for either input-oriented (R&D expenditure) or output-oriented (publication activity) measures of a firm's innovation effort, we test the relationship between co-publishing and innovation. We first test if research collaboration, as proxied by co-publishing, affects the probability of firms to innovate. We then investigate whether collaborating firms improve their innovation intensity; that is, whether the intensity of innovation activity is positively correlated with academic knowledge spillovers from collaboration. Consequently, our first research hypothesis reads as follows:

H1a *Firms whose scientists conduct co-publishing activity with academia increase their probability of being innovative (industry extensive patenting margin).*

[1] Krieger et al. (2021) identified favourable patterns in publishing within basic research journals when contrasted with those concentrated on applied research, as well as in collaborative publishing with academic partners versus solitary publication endeavours.

H1b *Firms whose scientists conduct co-publishing activity with academia improve their innovation intensity (industry intensive patenting margin).*

In more detail, as a first step of our analysis we aim to measure how innovative a firm is by focusing on two different dimensions: (a) their probability to innovate and (b) the extent to which they innovate (see Table 1). Therefore, we measure the effect of collaboration alternatively: *i*. on the industry extensive patenting margin (H1a), i.e., the probability that a firm that collaborates with university scientists starts being innovative; *ii*. on the industry intensive patenting margin (H1b), i.e., the intensity of the firm's innovation activity (see Table 1).

2.2 U-I collaboration and innovation performance: the role of time.

As previously mentioned, when dealing with biotech, chemical, and pharmaceutical firms, co-publishing is a particularly relevant proxy for knowledge transfer. It allows firms' scientists to enter the scientific network, access leading-edge research knowledge, take advantage of academic research infrastructure (Cunningham & Gök, 2012; Cunningham et al., 2016),

Table 1 Summary of research hypotheses, main covariates, and models

		Dependent variables		
		(a)	(b)	
Hypotheses	Main covariate	Patent (dummy = 1 if number of patents > 0)	Number of patents	Model
H1a	Number of co-publications (number co-publications, in ln)	Firms whose scientists conduct co-publishing activity with academia increase their probability of being innovative		Probit
H1b	Number of co-publications (number co-publications, in ln)		Firms whose scientists conduct co-publishing activity with academia improve their innovation intensity	Negative binomial
H2	Up to three leads of number of co-publications (number co-publications, in ln)	Co-publications have an "anticipatory effect" on biopharmaceutical firms' innovation performance		Probit, negative binomial, and dynamic difference-in-differences

H1a: Firms whose scientists conduct co-publishing activity with academia increase their probability of being innovative

H1b. Firms whose scientists conduct co-publishing activity with academia improve their innovation intensity

H2: Co-publications have an "anticipatory effect" on biopharmaceutical firms' innovation performance and exploit positive spillovers from the basic research typically conducted within academia. In this regard, when co-publishing is used as a proxy for collaboration, there is an important issue to account for concerning the timing effect of knowledge production and diffusion overlooked by the previous literature. Such an effect might be postponed or anticipated.

On the one hand, one might expect that firms postpone patenting (patent filing) to the publication of co-published papers using 'defensive publication' as a complementary part of a firm's overall IP protection strategy. Rotolo et al. (2022) point out that only small portion of the studies (about 20.7%) they examined delves into defensive 'publishing strategic' behavior and these contributions primarily consist of conceptual discussions or modelling attempts, indicating a lack of empirical examination.

Scientific publications from a firm tend to pose a greater challenge to the novelty of patent applications than other forms of defensive publishing (Della Malva & Hussinger, 2012). Several studies have investigated how, strategically disclosing information before patenting through publications, firms can influence prior art, effectively restricting competitors from patenting similar inventions. This strategy can serve as a proactive measure to protect intellectual property rights. According to Rotolo et al. (2022), defensive publishing strategies serve various purposes in competitive landscapes: extending patent races; reducing expected patent value; broadening patent scope; and preventing the privatization of inventions. Firstly, they can compel leading rivals to invest more resources in R&D, consequently narrowing the technical gap between competitors. Laggards, in particular, may resort to defensive publishing as their chances of overtaking the leader diminish. However, this strategy can backfire, as it may inadvertently provide critical information to the leading firm, accelerating its R&D progress. Secondly, leading firms may use defensive publishing to deter laggards from intensifying their efforts in a patent race, potentially forcing them out of the competition. Lastly, selective scientific disclosures can broaden the scope of existing patents, making it harder for rivals to patent incremental advancements and reducing the need for extensive patenting. This dual strategy is cost-effective and can safeguard a firm's freedom to exploit its R&D outcomes. Indeed, defensive publishing offers protection against risks associated with secrecy, such as reverse engineering and the mobility of researchers, allowing firms to benefit from their innovations across multiple markets at a lower cost.

Alternatively, one might assume that co-publications anticipate patent filing. Given the intellectual property law, private companies need to avoid publishing any information about their invention before filing the patent application, as any disclosure concerning the invention/new technology might undermine its novelty and compromise the probability of the firm obtaining a patent. Even though in the European Union there are two "non-prejudicial disclosures" under which public disclosure is allowed (i.e., evident abuse by a third party and presentation in official international exhibitions), patenting firms may allow their research (including that arising from collaboration with academics) to be published in scientific and academic journals only after patent filing, which guarantees a priority date to be claimed. By focusing on the peculiarities of the sector, support for our hypothesis is provided by Sternitzke (2010: page 816), who suggests that "the stream of papers following the basic patent and published by the same firm is primarily clinical". Such evidence suggests that, in the biopharmaceutical industry, publications ex-post reveal the knowledge generated by firms and, in the case of co-authored publications, the existence of knowledge generated by previous U-I collaborations.

Summing up, a co-authored paper can be regarded as the 'delatentisation' of a pre-existing research collaboration. We presume that the effect of this collaboration is anticipated with respect to the evidence of joint work (as represented by the publication date in WOS). Firms can capture positive knowledge spillovers from the collaborative research process when the cross-fertilization of ideas and knowledge is realized (i.e., during the elaboration of the study). Once joint research officially appears in a co-authored publication, most of the knowledge flow has already taken place, and co-publishing only represents its manifestation. Thus, we expect that U-I collaboration will affect patenting earlier than its manifestation in the form of a co-authored work indexed in WOS. By exploiting the panel dimension of our dataset, we can determine the timing of the relationship between collaboration and innovation. In conclusion, while hypothesis H1a and H1b test the overall relationship between collaboration and innovation (industry intensive and extensive margin), hypothesis H2 takes a step forward and disentangles this effect over time testing the hypothesis that patent filing anticipates the appearance of co-published research.

From an empirical standpoint, we test for this "anticipatory effect" including forwarded values of our co-publishing variable (as described in Sect. 3.2). We assume that a co-authored article might take up to three years to be published and appear in WOS. We formulate the second hypothesis as follows:

H2 *Co-publications have an "anticipatory effect" on biopharmaceutical firms' innovation performance.*

Table 1 summarises our research hypotheses in relation to the dependent variables, main covariates, and the estimated models.

3 Data and empirical strategy

3.1 Variables and descriptive statistics

Our analysis focuses on the period 2000–2010 and relies on data from different sources. Data on patents and firm characteristics were retrieved from the dataset developed by Lotti and Marin (2013), which combines information from PATSTAT and the AIDA–Bureau van Dijk dataset.[2] We integrated this information with data on U–I co-publications from the dataset of Giunta et al. (2016). The latter retrieved publications from the ISI Web of Science database and identified articles that were co-authored by at least one academic. Firms in the biopharmaceutical industry were identified based on the ATECO classification system.[3]

[2] The AIDA–Bureau van Dijk dataset covers firms of different sizes, ranging from small and medium-sized enterprises (SMEs) to large multinational corporations. It does not include micro enterprises that, although relevant in the overall Italian industrial structure, are less prevalent in the biopharma industry (the average dimension of firms is 131.2 employees in the pharmaceutical industry and 26.3 employees in the chemical against 10.1 in the manufacturing sector).

[3] ATECO is a classification of economic activities (in Italian, ***ATtività ECOnomiche***) adopted by the Italian national institute of statistics (Istat). Following Giunta et al. (2016), we included in our selection the following ATECO codes: 'production of chemical products' (20), 'production of pharmaceutical products' (21), 'R&D in biotechnologies' (72.11), and 'pharmacology' (72.19.09). The biopharma perimeter identified by Giunta et al. (2016) included also 'cultivation of healing herbs' (01.28). Nevertheless, missing data on some of the variables adopted in the parametric analysis prevented us from considering such sector. The number

Our dependent variable was proxied by a dummy variable assuming a value of 1 if firm *i* applies for (or owns) at least one patent at time *t*, and zero otherwise (to estimate the influence of collaboration on the probability of patenting) or by the number of patent applications of firm *i* at time *t,* to estimate the effect of collaboration on a firm's innovation intensity (source: PATSTAT).

We measured the impact of U–I collaboration on firms' innovation capabilities (H1a and H1b) by adopting as the main covariate the logarithm of the number of publications that firms' employees have co-authored with scholars from universities (*no. of co-publications*, ln; source: ISI Web of Science). Although co-publishing, as described in the previous paragraphs, is the most suitable U-I interaction measure for the case at hand, there are other relevant forms of U-I collaboration such as co-patenting.[4]

Following Autor (2003), we included the leads of this collaboration proxy to capture the effect of partnerships not yet signalled by a co-authored paper, in addition to contemporary co-publication activity (H2).

We took into account firm characteristics (source: AIDA–Bureau van Dijk), which may have influenced the firms' ability to acquire new knowledge and, consequently, their patenting activities. More precisely, we considered the most relevant characteristics of a firm, such as: *i*) *R&D expenditure*, as a proxy of a firm's absorptive capacity (Arundel & Geuna, 2004; Cohen & Levinthal, 1990); *ii*) firm size, proxied by the firm's *number of employees*; *iii*) *capital stock*; *iv*) *value-added*; *v) firm's age; vi*) *regional dummies* (the NUTS-1 location of firms to account for macroregional heterogeneity); *vii*) *no. of scientific publications* that is an output-oriented measure of R&D complementing the input-oriented measure provided by firms' R&D expenditure which allows our main covariates to capture the innovation effect associated only to U-I collaboration; *viii*) stock of *previous collaborations* with academia to control for the shared knowledge that took place in previous years and that might be associated with innovation activity as the U–I partnerships developed over the years might have a boosting (cascade) effect on today firms' knowledge-generation ability[5]; *ix*) sectoral dummies to absorb heterogeneity between firms involved in the production of chemical products, those producing pharmaceutical products and firms in pharmacology sector.

Table 2 describes the variables used in the analyses, along with the sources of the data.

Table 3 reports descriptive statistics for all the variables employed in the analyses. The yearly number of patent applications of the average firm in the sample is slightly higher than 1. The distribution is quite skewed, showing a relatively high standard deviation and a

of firms in the selected ATECO codes in the period 2000-2010 resulting in the comprehensive AIDA BvD dataset is 3294. However, most of such firms lack information for all the relevant information included in our empirical analysis and our estimation sample reduces to 513 firms. Although representing 15.6% of all registered firms, the sample we consider for our analysis is highly representative: they represent 59.9% of total employment, 61.8% of total assets and 64.0% of value added in biopharma in 2000.

[4] As mentioned above, consolidated literature identifies several key modes of university-industry (U-I) interactions. Among the most widely recognized are meetings and conferences, consultancy and contract research, the establishment of physical facilities, training programs, joint research agreements, joint publications, and joint patents (D'Este & Patel, 2007; Link et al., 2007; Lööf and Broström, 2008). Among these, co-patenting is a relevant one for the industry under investigation. However, co-patenting in Italy is a limited/elitist phenomenon which involves few specialized companies, such that reliance is possibly more on basic research and cutting-edge scientific solutions (Cerulli et al., 2021). On the contrary, co-publishing is a much more evenly used type of collaboration that is not confined to particular kind of firms, thus resulting more reliable for generalization of results in the science-based industry.

[5] In order to capture its cumulated effect, the variable is not discounted to account the effect of time.

Table 2 Description of variables

Variables	Description	Source
Dependent variables (pat)		
Patents (dummy)	Dummy variable equal to 1 when the number of patent application is higher than 0 (and 0 otherwise)	PATSTAT
No. of patents	Number of patent applications submitted by firms (count)	PATSTAT
Main covariates		
No. of co-publications (ln) *CP*	The number of publications that firms' employees have co-authored with university researchers	ISI Web of Science
Control variables (*X*)		
Previous collaborations (cumul. no. of co-publications, ln)	Lagged cumulated number of co-published papers. This variable proxies for the stock of knowledge obtained in past joint U-I projects	Own computation based on ISI Web of Science
R&D expenditure (ln)	Value of R&D expenditure (million €) according to firms' balance sheets (part of intangible fixed assets)	AIDA–Bureau van Dijk
No. of scientific publications (ln)	The total number of publications authored by firms	ISI Web of Science
No. of employees (ln)	Firms' sizes, as proxied by the number of employees	ASIA-ISTAT
Capital stock (ln)	Stock of fixed physical capital (million €)	AIDA–Bureau van Dijk
Value-added (ln)	Firms' value added (million €)	AIDA–Bureau van Dijk
Firm's age (ln)	No. of years obtained by subtracting firms' establishment year from the current year	Own computation based on AIDA–Bureau van Dijk
Regional dummies (North-West; North-Est; Centre; South; Isles)	NUTS-1 region in which the firm is located	AIDA–Bureau van Dijk
Sectoral dummies	ATECO 2-digits sector of firms	AIDA–Bureau van Dijk

maximum value of 193. On average, firms own patents in 22.4% of the cases. Such numbers are driven by the sample of firms that publish co-authored papers, as the mean value of their patents is approximately 21.3 per year, compared to the mean value of 6.25 recorded for firms not publishing joint papers with researchers in academia.

On average, the number of yearly publications is slightly lower than one (0.93). The correlation between the number of publications and the number of co-publications is evident by comparing the values of the former variable between the two subsamples: firms that co-publish have an average number of publications equal to 5.87, while firms not involved in collaborations record an average number of co-publications equal to 0.65. The descriptive data suggest that, on average, firms involved in co-publications invest more in R&D

(0.283 million Euros) than those not involved (0.194 million Euros). This is consistent with the firms' need to acquire an adequate level of absorptive capacity to effectively interact with academia. The statistics relative to the number of employees and capital stock show a sizeable difference between the two groups: firms that co-publish with universities are, on average, larger and have higher cumulative stock of fixed physical capital. Moreover, the average value added by firms that co-author with academic scholars at least once is approximately four times the value recorded by firms with no co-publications. In addition, the average age of firms that co-publish is approximately 27.8 years, whereas that of firms that do not co-publish is 25 years.

Table 3 Descriptive statistics

	Variable	Obs	Mean	Std. Dev	Min	Max
Full sample	Patents (dummy)	3717	0.224	0.417	0.000	1.000
	No. of patents	3717	1.110	7.898	0.000	193.000
	No. of co-publications	3717	0.174	1.123	0.000	19.000
	No. of scientific publications	3717	0.926	2.946	0.000	40.000
	Previous collaborations	3717	0.808	5.532	0.000	105.000
	R&D expenditure (million €)	3717	0.199	1.372	0.000	30.987
	No. of employees	3717	215.242	662.836	1.000	11,442.000
	Capital stock (million €)	3717	45.481	222.742	0.000	3956.503
	Value-added (million €)	3717	23.525	75.092	0.000	1081.418
	Firm's age	3717	25.175	19.650	0.000	102.000
	North-West	3717	0.586	0.493	0.000	1.000
	North-East	3717	0.195	0.396	0.000	1.000
	Centre	3717	0.162	0.369	0.000	1.000
	South	3717	0.041	0.198	0.000	1.000
	Isles	3717	0.015	0.123	0.000	1.000
	Production of chemical products	3717	0.573	0.495	0.000	1.000
	Pharmaceutical products	3717	0.314	0.464	0.000	1.000
	Pharmacology	3717	0.113	0.317	0.000	1.000
No. of co-publications in t0 = 0	Patents (dummy)	3521	0.206	0.405	0.000	1.000
	No. of patents	3521	0.811	6.250	0.000	193.000
	No. of scientific publications	3521	0.651	2.272	0.000	35.000
	Previous collaborations	3521	0.124	0.881	0.000	17.000
	R&D expenditure (million €)	3521	0.194	1.351	0.000	30.987
	No. of employees	3521	186.376	553.282	1.000	11,442.000
	Capital stock (million €)	3521	38.232	176.322	0.000	3696.245
	Value-added (million €)	3521	19.143	56.668	0.000	962.102
	Firm's age	3521	25.030	19.488	0.000	102.000
	North-West	3521	0.597	0.491	0.000	1.000
	North-East	3521	0.200	0.400	0.000	1.000
	Centre	3521	0.147	0.354	0.000	1.000
	South	3521	0.040	0.196	0.000	1.000
	Isles	3521	0.016	0.126	0.000	1.000
	Production of chemical products	3521	0.596	0.491	0.000	1.000
	Pharmaceutical products	3521	0.292	0.455	0.000	1.000
	Pharmacology	3521	0.112	0.316	0.000	1.000

Table 3 (continued)

	Variable	Obs	Mean	Std. Dev	Min	Max
No. of co-publications in t0 = 1	Patents (dummy)	196	0.536	0.500	0.000	1.000
	No. of patents	196	6.474	21.285	0.000	186.000
	No. of scientific publications	196	5.872	6.797	1.000	40.000
	Previous collaborations	196	13.112	20.213	1.000	105.000
	R&D expenditure (million €)	196	0.283	1.699	0.000	21.542
	No. of employees	196	733.808	1600.386	3.000	10,465.000
	Capital stock (million €)	196	175.702	605.195	0.047	3956.503
	Value-added (million €)	196	102.246	207.155	0.115	1081.418
	Firm's age	196	27.796	22.263	1.000	93.000
	North-West	196	0.403	0.492	0.000	1.000
	North-East	196	0.107	0.310	0.000	1.000
	Centre	196	0.434	0.497	0.000	1.000
	South	196	0.056	0.231	0.000	1.000
	Isles	196	0.000	0.000	0.000	0.000
	Production of chemical products	196	0.168	0.375	0.000	1.000
	Pharmaceutical products	196	0.704	0.458	0.000	1.000
	Pharmacology	196	0.128	0.334	0.000	1.000

Approximately 60% of our observations pertain to firms located in northwest Italy, while less than 6% of the firms are in the South and the Isles. The distribution of most firms involved in collaborations with universities (more than 83%) is concentrated, almost equally, in the northwest and central macro-regions. None of these firms are in the Isles. Such a territorial polarized distribution is explained by the well-known north–south divide that characterises the Italian industrial structure and, more generally, the Italian economy. As far as the biopharmaceutical industry is concerned, there are two important clusters in Italy: Lombardy (north) and Latium (centre). The Latium region, in particular, accommodates one of the most important agglomerations of biopharmaceutical firms in Italy[6] (multinationals and SMEs), as well as a considerable number of outstanding universities and public research centres.[7] By looking at the sectoral distribution of firms, about 57.3 % of firms are involved in the production of chemical products, about 31.4 % in the pharmaceutical production, while 11.3 % is represented by pharmacology firms. When focusing on the subsample of firms that co-publish, the distribution changes and the shares become 16.8 %, 70.4 % and 12.8 %, respectively.

3.2 Methodology

We adopted a parametric approach, using both probit and negative binomial estimators, to determine whether firms involved in co-publications with universities tend to register more patents. By adopting co-publishing as a proxy for U–I collaborations, we were able to investigate whether involvement in such collaboration increases the probability of innovation and the number of patents.

Our baseline model is:

[6] This is in addition to Lombardy and Tuscany, in terms of public and private R&D spending and incidence of value added (for the Latium case, 25% of total manufacturing).

[7] Perhaps owing to the presence in this region of the capital city, Rome.

$$pat_{it} = \beta_{CP}\boldsymbol{CP_{it}} + \beta_X X_{it} + \varepsilon_{it} \tag{1}$$

where pat_{it} is a dummy variable equal to one when firm i has at least one patent at time t (*patents*, dummy) or alternatively, the number of patents of firm i at time t (*no. of patents*). CP_{it} represents the logarithm of the number of publications co-authored by firm employees and academic researchers (*no. of co-publications*, ln).

As previously mentioned, we included a group of control variables X_{it}, such as the *no. of scientific publications*, firms' *R&D expenditure*s, *no. of employees*, *firm age*, *capital stock, value-added*, *previous collaborations*, and regional, sectoral and year-fixed effects. We also use firm-clustered standard errors.

As we come to hypothesis H2 and test whether an "anticipatory effect" exists (hypothesis H2), we include in our estimated model a set of forwarded CP_{it} variables, which allows us to capture the effect of collaborations on innovation (patent filing) just before the observation of a co-publication (our proxy for collaboration). To detect the presence of this "pre-treatment" effect we follow Autor (2003) and, from the baseline model (Eq. 1), specify our estimated equation as follows:

$$pat_{it} = \beta_{CP}\boldsymbol{CP_{it}} + \sum\nolimits_{j=1}^{3} \beta_{CP,lead_j}\boldsymbol{CP_{it+j}} + \beta_X X_{it} + \varepsilon_{it} \tag{2}$$

We included up to three leads of the co-publication variable ($CP_{it+1}, CP_{it+2}, CP_{it+3}$), assuming that the process from actual collaboration to the inclusion of a co-authored paper in the Web of Science database might take up to three years.

We also perform a Dynamic Difference-in-Differences (DDiD) model to investigate the presence of pre- and post-treatment effects of the binary time-varying treatment *co-publication* dummy on the number of patent applications by following the DDiD approach of Cerulli and Ventura (2019) and Cerulli et al. (2021). If all leads are statistically non-significant it would confirm that the latent collaboration existing a few years before co-publication, influences firms' innovation performance (see Section 5 for a full description of the model).

4 Results

This section presents the results of our empirical analysis employing probit and negative binomial models, while the next provides some robustness analyses.

Table 4 presents the estimates of our probit model, in which the dependent variable (*patents*) is binary and assumes a value equal to 1 when the company has at least one patent, and 0 otherwise. These results show that co-publishing (*no. of co-publications*, ln) is positively associated with the probability of innovation.[8] U–I collaborations increase the probability of innovation, because both the contemporary and forwarded co-publication dummies are positive and strongly significant. Such a relationship is particularly significant for forwarded variables that capture the "anticipatory effect" of co-publications and—in virtue of their cor-

[8] The same results are obtained when we use a dummy variable that assumes value of 1 if the company has at least one co-publication and 0 otherwise as a covariate. Results are not reported here and are available upon request.

relation with contemporary values—tend to absorb the significance of the coefficient associated to the number of co-authored papers at time *t*. In order to consider the overall effect of forwarded variables, we include in all estimates their linear combination. Firms increasing the number of co-publications by 10%—thereby intensifying their ties with academia—increase their innovation intensity by 26 to 35%, particularly during the three years before the publication of joint work (columns 4 and 7, respectively). The coefficient associated with *previous collaborations* is always positive and significant in specifications 1, 2, 5 and 8, showing mild evidence that firms with a higher stock of previous collaborations have a higher probability of patenting. When statistically different from zero, patenting probability shows up to 1% elasticity to our *previous collaborations* variable. In such setting, our input-oriented measure of innovation, *R&D expenditure*, as well as *value-added*—that shows highly significant coefficients—are positively associated with the probability of patenting. Our output-oriented measure of innovation, the *no. of scientific publications*, is positively associated with the dependent variable, albeit not always in a statistically significant way, while the coefficient associated with *capital stock* and *firm size* is positively associated with innovation intensity, although not statistically significant. Firms' age is negatively associated with patenting intensity, suggesting, as expected, that more recently established firms have higher incentives to patent than incumbent firms.

Table 5 presents the negative binomial estimates to investigate whether different intensities of co-publishing activity affect a firm's innovation intensity.

Accordingly, we analysed the impact of (log of) the *no. of co-publications* on firms' innovation intensity (*no. of patents*). Our proxy for U–I collaboration is positively associated with the number of patents, particularly when the leads of the variable are included. Most of the coefficients capturing the "anticipatory effect" of co-publications are strongly significant and positive. This result indicates that the positive effect of collaboration might start manifesting a couple of years before the publication of a co-authored article, confirming the existence of a knowledge spillover that is, most often, *ex-post* delatentised. The existence of an "anticipatory effect" is confirmed, in particular, in virtue of the statistically significance of leads' linear combination. As shown in Table 4, the magnitude of the linear combination tended to increase with the inclusion of leads up to three years ahead.

When examining the role of knowledge cumulated in previous years' collaborations (measured by the variable *previous collaborations*), we find weak evidence that firms with high lagged cumulative number of collaborations tend to register more patents. Our proxy for the mass of U-I collaborations previously cumulated shows coefficients which are not statistically significant. *Firm size* is relevant, whereas value-added is associated with the number of patent applications at the 10% significance level. As expected, and in line with the results presented in Table 4, firm age is negatively associated with our dependent variable while the *no. of scientific publications* (our output-oriented measure of innovation) is positively associated with the probability of applying for a patent.

Table 6 summarises the results in terms of the main hypotheses. Collaboration (measured using the logarithm of *the no. of co-publications*) plays a double role in firms' innovation process: it is crucial in boosting both the innovation capability and innovation intensity of firms (H1a and H1b) owing to the spillover effect generated by current partnerships.[9] Collaboration has an "anticipatory effect" on innovation when using co-publishing as a

[9] We have replicated the analysis adopting a dummy equal to 1 if a firm co-authored at least one publication at time *t*, and 0 otherwise, as main covariate. The results are coherent with those reported in the paper.

proxy (H2). Once the forwarded values of the collaboration variable are included in the regression, their coefficients are statistically significant, while contemporaneous regressors become non-statistically significant, signalling how the relationship between U–I collaboration and innovation precedes the manifestation of the joint published article. Therefore, the biopharma industry pursues the strategy of patent filing first and we find no evidence of "defensive publication".

5 Robustness

To confirm the robustness of our analysis, we performed a set of tests and robustness analyses: i) first, we check for endogeneity among our main covariates; ii) second, we address overdispersion and an excess of zeros; iii) third, we run a placebo test adopting time lags instead of time forwards; iv) lastly, we perform a Dynamic Difference-in-Differences (DDiD) model.

As the first robustness analysis, we performed an instrumental variable (IV) probit model and computed the Wald $\chi 2$ to test the exogeneity of our main covariates. Applying a standard approach, we instrumented our main covariates with their lagged values since they were sufficiently exogenous to the dependent variable and correlated to the instrumented ones. The pairwise correlation between co-publication lags and the dummy dependent variable is between 0.024 and 0.035, while the correlation between co-publication lags and the count dependent variable is between 0.049 and 0.089. This lack of correlation is also highlighted by the placebo test (see below). Meanwhile, the correlation between lags and leads is high, usually above 0.5. We instrumented the contemporaneous co-publication variable and its leads with the most recent time lags in each specification. The Wald $\chi 2$ statistics of the endogeneity test and the p-values are reported at the bottom of Table 4 and show that, in almost all specifications, the null hypothesis of exogeneity is accepted.[10] Therefore, our measure of collaboration can be treated as exogenous.

Second, we dealt with overdispersion and an excess of zeros. The Chi-bar^2 statistics for testing for the over-dispersion of our count dependent variable are reported at the bottom of Table 5, showing the appropriateness of choosing a negative binomial model relative to a Poisson model. We also ran models to control for both excess zeros and over-dispersion. Specifically, we first estimated a zero-inflated negative binomial (ZINB) model. In Table 8 *panel a* in the Appendix, we present the ZINB estimates for the same specifications reported in the first four columns of Table 5. Further, we also estimated a pseudo-Poisson maximum likelihood (PPML) model (see Table 8 *panel b* in the Appendix)[11] that allowed us to deal with the presence of many zeros. Overall, the ZINB and PPML models' results are largely in line with those reported in Table 5; therefore, we can consider our results from the negative binomial model as robust with respect to an excess of zeros.

Third, to further corroborate the results highlighted in Sect. 4, we replicate the probit and negative binomial estimates by adopting co-publication lags instead of time-forward variables to check whether such "placebo" variables lead to similar results despite being

[10] The only partial exception is represented by the specification in column (7) for which the null hypothesis is accepted at 5% significance level but slightly rejected at 10%.

[11] The overdispersion test reported in Table 5 suggests that we prefer the negative binomial to Poisson; we run PPML only as a check to deal with an excess of zeros.

Table 4 Probit estimates with patents (dummy) as a dependent variable and no. of co-publications (ln) as a main covariate

Dependent variable: patents (dummy)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
No. of co-publications (ln)	0.013**	0.007	0.002	-0.001						
	(0.005)	(0.004)	(0.005)	(0.005)						
No. of co-publications (1-y fwd, ln)		0.015***	0.011*	0.006	0.018***	0.011*	0.006			
		(0.005)	(0.006)	(0.008)	(0.006)	(0.007)	(0.009)			
No. of co-publications (2-y fwd, ln)			0.015***	0.010***		0.016***	0.009***	0.020***	0.011***	
			(0.004)	(0.003)		(0.003)	(0.003)	(0.003)	(0.003)	
No. of co-publications (3-y fwd, ln)				0.019***			0.019***		0.021***	0.025***
				(0.003)			(0.003)		(0.003)	(0.003)
Previous collaborations	0.010***	0.006**	0.004	0.003	0.008**	0.005	0.003	0.008*	0.004	0.007
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
Tot. no. of publications (ln)	0.007**	0.007**	0.006**	0.003	0.008**	0.007**	0.003	0.007**	0.003	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
R&D expenditure (ln)	0.003**	0.003**	0.002**	0.002*	0.003**	0.002**	0.002*	0.003**	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No. of employees (ln)	0.007	0.007	0.006	0.002	0.007	0.007	0.002	0.006	0.002	0.002
	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)	(0.016)	(0.015)	(0.016)	(0.016)
Capital stock (ln)	0.008	0.009	0.009	0.011	0.009	0.009	0.011	0.009	0.011	0.011
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)
Value-added (ln)	0.026***	0.025***	0.024***	0.026***	0.025***	0.024***	0.026***	0.025***	0.026***	0.026***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)
Firm's age (ln)	−0.033***	−0.031***	−0.031***	−0.030***	−0.031***	−0.031***	−0.030***	−0.032***	−0.030***	−0.030***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)	(0.009)
Linear combination of leads			0.026***	0.035***		0.027***	0.035***		0.032***	
			(0.005)	(0.009)		(0.006)	(0.009)		(0.005)	
N	3348	3348	3346	3000	3348	3346	3000	3346	3000	3000

Table 4 (continued)

Dependent variable: patents (dummy)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wald $\chi2$ test (exog)	0.717	0.843	2.94	2.569	1.555	1.356	6.363	2.526	1.647	1.403
Wald test p-value	0.397	0.656	0.401	0.632	0.212	0.508	0.095	0.112	0.439	0.236

Firm-clustered standard errors in parentheses ***$p<0.01$, **$p<0.05$, *$p<0.1$. Wald tests are performed on the IV probit estimates, with time lags as instruments. The coefficients are referred to as marginal effects

Table 5 Negative binomial estimates with number of patents as dependent variable and no. of co-publications (ln) as main covariate

Dependent variable: number of patents	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
No. of co-publications (ln)	0.061**	0.014	−0.006	−0.039						
	(0.029)	(0.027)	(0.027)	(0.031)						
No. of co-publications (1-y fwd, ln)		0.106***	0.085***	0.078***	0.111***	0.084***	0.070**			
		(0.026)	(0.024)	(0.027)	(0.027)	(0.024)	(0.027)			
No. of co-publications (2-y fwd, ln)			0.058**	0.022		0.056**	0.014	0.093***	0.033	
			(0.023)	(0.021)		(0.023)	(0.021)	(0.027)	(0.024)	
No. of co-publications (3-y fwd, ln)				0.100***			0.092***		0.108***	0.124***
				(0.030)			(0.030)		(0.028)	(0.029)
Previous collaborations (ln)	0.032	−0.002	−0.009	−0.024	0.002	−0.011	−0.030	0.016	−0.009	−0.000
	(0.026)	(0.028)	(0.028)	(0.030)	(0.029)	(0.030)	(0.031)	(0.028)	(0.030)	(0.030)
Total publications (ln)	0.084***	0.080***	0.078***	0.074***	0.082***	0.077***	0.070***	0.081***	0.073***	0.076***
	(0.022)	(0.023)	(0.023)	(0.024)	(0.021)	(0.022)	(0.023)	(0.021)	(0.022)	(0.022)
R&D expenditure (ln)	0.004	0.003	0.003	−0.001	0.003	0.003	−0.001	0.004	−0.001	−0.001
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
No. of employees (ln)	0.297**	0.293**	0.291**	0.271**	0.293**	0.291**	0.273**	0.292**	0.272**	0.271**
	(0.129)	(0.128)	(0.128)	(0.129)	(0.128)	(0.128)	(0.130)	(0.128)	(0.129)	(0.129)
Capital stock (ln)	0.102	0.106	0.107	0.110	0.105	0.107	0.110	0.105	0.110	0.109
	(0.112)	(0.113)	(0.112)	(0.122)	(0.112)	(0.112)	(0.122)	(0.112)	(0.121)	(0.119)
Value-added (ln)	0.198*	0.190*	0.187*	0.191*	0.190*	0.187*	0.191*	0.191*	0.193*	0.196*
	(0.105)	(0.105)	(0.105)	(0.108)	(0.105)	(0.105)	(0.109)	(0.105)	(0.108)	(0.108)
Firm's age (ln)	−0.302***	−0.301***	−0.305***	−0.305***	−0.302***	−0.304***	−0.303***	−0.308***	−0.306***	−0.306***
	(0.064)	(0.065)	(0.065)	(0.068)	(0.064)	(0.065)	(0.068)	(0.064)	(0.067)	(0.067)
Constant	−4.080**	−3.894**	−3.810**	−3.783**	−3.913**	−3.804**	−3.748**	−3.923**	−3.833**	−3.898**

Table 5 (continued)

Dependent variable: number of patents	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	(1.597)	(1.608)	(1.620)	(1.645)	(1.604)	(1.619)	(1.651)	(1.616)	(1.646)	(1.642)
Linear combination of leads			0.143***	0.200***		0.140***	0.175***		0.141***	
			(0.035)	(0.042)		(0.035)	(0.04)		(0.035)	
N	3348	3348	3346	3000	3348	3346	3000	3346	3000	3000
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi-bar2 test: alpha = 0	*2761.77*	*2729.20*	*2688.41*	*2408.39*	*2731.33*	*2688.52*	*2406.62*	*2695.98*	*2401.22*	*2401.46*
Prob > = chi-bar2	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*

Firm-clustered standard errors in parentheses ***$p<0.01$, **$p<0.05$, *$p<0.1$

Table 6 Summary of results

		Dependent variable		
		(a)	(b)	
Hypotheses	Main covariate	Patent (dummy = 1 if no. patents > 0)	No. of patents	Model
H1a	No. of co-publications (no. co-publications, in ln)	Yes		Probit
H1b	No. of co-publications (no. co-publications, in ln)		Yes	Negative Binomial
H2	Up to three leads of no. of co-publications (no. co-publications, in ln)	Yes		Probit, negative binomial, and dynamic difference-in-differences

H1a: Firms whose scientists conduct co-publishing activity with academia increase their probability of being innovative

H1b. Firms whose scientists conduct co-publishing activity with academia improve their innovation intensity

H2: Co-publications have an "anticipatory effect" on biopharmaceutical firms' innovation performance

specular to time leads. This exercise also allows us to exclude the presence of a 'defensive publication' strategy.

Table 7 reports our placebo test results with co-publication lags instead of the forward variables. Despite the linear combinations of the lagged number of co-publications (in log) reported in columns 4—as well as the 3-year lagged variable—being statistically significant at 90%, all the other coefficients of interest of our placebo test are statistically non-different from zero. The adoption of lagged variables, which might capture a delayed effect of U–I collaboration in the following years (patent filing occurring after co-publishing), does not provide convincing results and, on the contrary, supports the results reported in Section 4.

Finally, we investigate the presence of pre- and post-treatment effects of the binary time-varying treatment *co-publication* dummy on the number of patent applications by following the DDiD approach of Cerulli and Ventura (2019) and Cerulli et al. (2021).

DDiD estimates allow us to investigate whether a binary treatment for firm *i* at time *t* has pre- or post-treatment effects.

In this setting, we indicate D_{it} as:

$$D_{it} = \begin{cases} 1 \; if \; firm \, i \, has \, co - publications \, at \, time \, t \\ 0 \; if \; firm \, i \, has \, no \, co - publications \, at \, time \, t \end{cases} \tag{3}$$

Following Cerulli and Ventura (2019) and Cerulli et al. (2021), we include leads and lags in the regression to estimate the average treatment effect over time. The regression that allows the measurement of the "anticipatory effect" of the treatment and the post-treatment effect is specified as follows:

Table 7 Probit and Negative binomial estimates with time lag instead of time leads. *No. co-publications* (ln) as main covariate

Dependent variables:	Patents (dummy)				no. of patents			
	Probit	Probit	Probit	Probit	Negative binomial	Negative binomial	Negative binomial	Negative binomial
Covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No. co-publications (ln)	0.013**	0.011**	0.011*	0.007	0.061**	0.046*	0.040	0.036
	(0.006)	(0.006)	(0.006)	(0.006)	(0.029)	(0.027)	(0.026)	(0.030)
No. of co-publications (1-y lag, ln)		0.007	0.007	0.005		0.053	0.045	0.026
		(0.007)	(0.007)	(0.008)		(0.038)	(0.038)	(0.038)
No. of co-publications (2-y lag, ln)			0.007	0.006			0.030	0.030
			(0.006)	(0.006)			(0.029)	(0.026)
No. of co-publications (3-y lag, ln)				0.012*				0.052
				(0.007)				(0.032)
Previous collaborations (ln)	0.010**	0.007	0.004	0.000	0.032	0.005	-0.006	-0.025
	(0.004)	(0.006)	(0.007)	(0.008)	(0.026)	(0.037)	(0.042)	(0.046)
Tot. no. of publications (ln)	0.007**	0.007**	0.008**	0.008**	0.084***	0.084***	0.089***	0.090***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.022)	(0.022)	(0.023)	(0.024)
R&D expenditure (ln)	0.003**	0.003**	0.003**	0.003**	0.004	0.004	0.005	0.005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.008)	(0.008)	(0.008)
No. of employees (ln)	0.007	0.007	0.006	0.010	0.297**	0.295**	0.311**	0.318**
	(0.014)	(0.014)	(0.015)	(0.016)	(0.129)	(0.129)	(0.136)	(0.148)
Capital stock (ln)	0.008	0.009	0.007	0.011	0.102	0.103	0.073	0.084
	(0.008)	(0.008)	(0.008)	(0.008)	(0.112)	(0.111)	(0.109)	(0.120)
Value-added (ln)	0.026*	0.026*	0.026*	0.018	0.198*	0.197*	0.194*	0.168
	(0.014)	(0.014)	(0.014)	(0.013)	(0.105)	(0.105)	(0.107)	(0.106)

Table 7 (continued)

Dependent variables:	Patents (dummy)				no. of patents			
	Probit	Probit	Probit	Probit	Negative binomial	Negative binomial	Negative binomial	Negative binomial
Covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm's age (ln)	−0.033***	−0.032***	−0.034***	−0.035***	−0.302***	−0.301***	−0.304***	−0.290***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.064)	(0.064)	(0.066)	(0.071)
Linear combination of leads			0.014	0.023*			0.075	0.108
			(0.011)	(0.014)			(0.054)	(0.068)
N	3348	3346	2989	2589	3348	3346	2989	2589
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Firm-clustered standard errors in parentheses ***$p<$ **$p<0.05$, *$p<0.1$. Probit coefficients are referred to marginal effects

$$pat_{it} = \mu_{it} + \sum\nolimits_{k=1}^{3} \beta_{D,lag_k} D_{it-k} + \beta_{D,t} D_{it} + \sum\nolimits_{j=1}^{3} \beta_{D,lead_j} D_{it+j} + \beta_X X_{it} + \varepsilon_{it} \quad (4)$$

If $\beta_{D,lead_j} \neq 0$ (the coefficients capturing the effect of the leads are statistically not different from zero), the treatment delivered at time t affects the outcome at time $t - j$; if $\beta_{D,t} \neq 0$, the treatment delivered at time t affects the outcome at time t; and if $\beta_{D,lag_k} \neq 0$ (the coefficients capturing the effect of the lags are statistically not different from zero), the treatment delivered at time t affects the outcome at time $t + k$.

However, a fundamental step of the DDiD approach is to check the so-called "parallel trend assumption" that allows us to detect causality between treatment and outcome. The assumption is respected if all the leads included in the regression are jointly zero. As our findings in Section 4 show the presence of an "anticipatory effect", we expect to reject the null hypothesis that all leads are statistically non-significant. This would impede a causal interpretation of the post-treatment pattern but, conversely, would confirm that the latent collaboration, existing a few years before co-publication, influences firms' innovation performance.

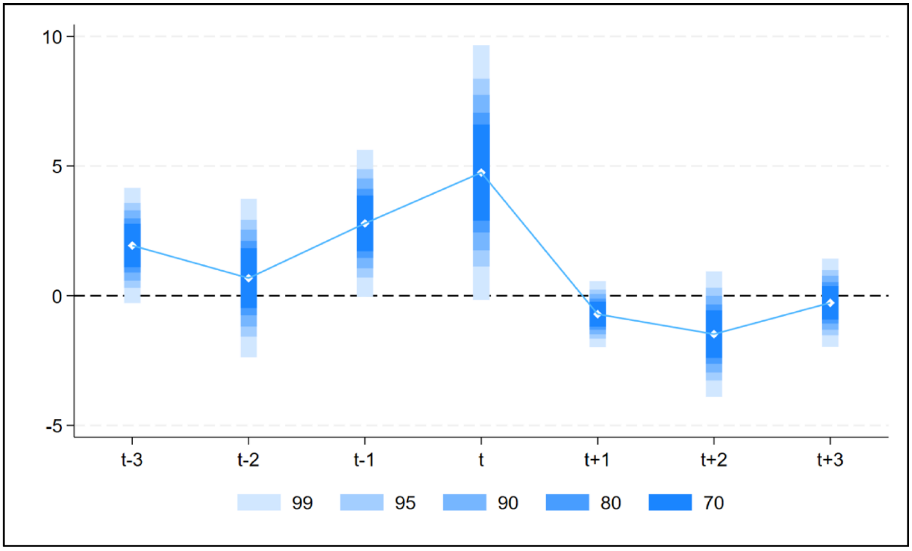
Figure 1 shows the output of DDiD estimates.

Both the graph and the parallel trend statistics show that the leads—the variables that capture the "anticipatory effect" of the treatment—reject the null hypothesis that they are jointly equal to zero. By contrast, the coefficients associated with the forward variables at time t-3 and t-1 are positive and statistically significant at 5 % level. Such empirical evidence, consistent with our research hypotheses, confirms that innovation activity, as captured by the number of patents, is influenced by a pre-treatment effect derived from the knowledge spillover arising from U–I collaborations, months or years before such collaboration can lead to the publication of a co-authored paper.

However, the parallel trend test cannot distinguish between diverging trends and the "anticipatory effect"; thus, the rejection of the null hypothesis of the parallel trend test might signal the existence of an "anticipatory effect" or diverging trends, or both. To deal with this point and check whether the test rejection is linked to the presence of anticipatory effects, we tested whether treated and control observations do differ with respect to covariate characteristics in the pre-treatment period. Focusing on the observations included in the DDiD estimates, we checked that the test of the balancing property of the propensity score is satisfied, leading us to believe that the parallel trend test's failure can be imputed to the presence of an "anticipatory effect". We controlled for many of the most relevant confounding factors that could determine differences in trends. The balancing confirms that the pre-treatment treated, and control groups are very similar to the X variables.[12] On this basis, we can reliably ignore the notion that the rejection of the parallel trend test is ascribable to diverging trends; on the contrary, it can be reasonably taken as evidence of an anticipation effect.

Overall, our robustness checks bolster the evidence provided in Section 4. Our hypotheses—H1a and H1b—are verified for every specification. Our "placebo" test and DDID analysis strongly support evidence on the timing of the effect of collaboration on innovation: innovation activity precedes the manifestation of collaboration as measured by the objective measure of co-authored articles (hypothesis H2).

[12] Partial exceptions are represented by the previous collaborations proxy and one macro-region dummy for only 1 over 9 propensity score blocks.



'Parallel trend' **not** passed.
F(3,23) = 3.12
Prob > F = 0.0456
Number of observations = 3,348
Outcome variable: *no. of patents*. Treatment: *co-publications* (dummy). Covariates: *R&D expenditure* (ln), *no. of employees* (ln), *capital stock* (ln), *value-added* (ln), *firm's age* (ln), *previous collaborations* (ln), *no. of publications* (ln). Dummy variables: *sector, region, and time dummies*.

Fig. 1 Dynamic difference in difference output

6 Discussion and conclusions

The main objective of this study was to investigate the relationship between U-I interaction—as measured by co-authored articles—and firms' innovation activity focusing on the role of time in the co-publishing-innovation relationship.

We focus on the biopharmaceutical industry, as it extensively engages with public research, given its science-based nature and the need to acquire external knowledge. For this industry, co-authored articles represent a knowledge channel mode capable of transferring knowledge (Cockburn & Henderson, 1998). The latter is particularly suitable as a proxy variable, as firms publish intensively, and a sizeable share of publications is co-authored with scientists from academia and public research centres. The data used in this study cover a period of ten years (2000–2010) and were retrieved from three main sources: AIDA–Bureau van Dijk for firm characteristics, PATSTAT for patent data, and ISI Web of Science for co-published papers, by merging the datasets of Lotti and Marin (2013) and Giunta et al. (2016).

Our empirical evidence suggests a clear positive role of U-I interaction in enhancing firms' innovation capability and the intensity of innovation activity. Furthermore, we highlight the "anticipatory effect" of co-publishing on a firm's innovative performance. Co-published articles represent the manifestation of a collaboration whose positive spillovers were captured by the firm years before the appearance of the joint article.

While our analysis results to be robust to many empirical methods and robustness checks, some limitations remain. First, we are aware that patents are an imperfect measure of innovation. Indeed, a substantial body of literature distinguishes patents as indicators of "invention" rather than "innovation," as not all patents translate into commercialized products that benefit consumers. Therefore, also other measures of innovation should be considered as our dependent variable. Nevertheless, as highlighted by Almeida et al. (2011), patent counts have proven to be effective indicators of innovation, and alternative metrics of innovation, such as the development of new products, show a strong correlation with our measure.

Second, we acknowledge that there might not be a univocal order between co-publications and patent activity: in some circumstances, the link between the two can suffer endogeneity biases. Although in our study we robustly found that our *ex-post* revealing proxy of collaboration (co-publications) has an impact on both the probability of applying for a patent and the number of patent applications, and that no reverse causality is found, we expect non-univocal results in other sectors. In fact, one of the elements that led us to formulate the hypothesis on the presence of anticipatory effect is the fact that papers following the basic patent and released by the same bio-pharma company are mainly clinical (Sternitzke, 2010). This suggests that this could be specific to firms that publish after testing—and before commercializing—products they have patented, thus to firms operating in specific fields.

This study makes a significant contribution to the existing literature by empirically examining the temporal dynamics of the relationship between collaboration and innovation—an aspect largely overlooked in prior research (e.g., Almeida et al., 2011; Cockburn & Henderson, 1998; Leten et al., 2022; McKelvey & Rake, 2016). Specifically, we analyze the temporal correlation between academic publishing and patenting, ultimately refuting the hypothesis of 'defensive publication' as a complementary component of biopharmaceutical firms' broader intellectual property (IP) protection strategy (Della Malva & Hussinger, 2012; Rotolo et al., 2022 and references therein). Our findings offer valuable insights into the IP protection strategies employed by biopharmaceutical firms and provide important implications for policy formulation.

The first policy implication concerns the role of public policy in fostering U-I collaborations. Public policies addressing U-I links are crucial for promoting the innovation performance of science-based industries, such as biopharma. Research and innovation in the biopharmaceutical industry are decidedly risky, span long periods, and incur remarkably high costs (Sternitzke, 2010). Therefore, firms' private investments can be suboptimal, whereas the economic and societal returns of new drug discoveries may be very large. This aspect has already gained the attention of European policymakers in the Horizon 2020 objectives. Recent events related to the COVID-19 pandemic and the vaccine race have shed new light on the need for public intervention to foster public–private partnerships, as these partnerships may reduce uncertainty and accelerate research and innovation by pooling resources and gathering critical mass. The European Commission recognises that diverse sources of funding are essential for innovation: 'Horizon Europe, the Cohesion Policy, the European Defence Fund, public–private and public–public investment partnerships such as the Innovative Health Initiative, and national schemes are important enablers for R&D, including for SMEs and academia' (EU Commission, 2020a: page 11). Further, one of the main objectives of the European Partnership for Innovative Health (the Initiative) is to 'integrate fragmented health research and innovation efforts across sectors and technologies, academia, and industry/public and private stakeholders' (EU Commission, 2020b: page 15). To this end, cooperation between health systems and private companies can also be pursued through public procurement, as public buyers can establish partnerships for the development, manufacturing, and subsequent purchase of medicines with limited demand (EU Commission, 2020a). Within this framework, our results show how knowledge transfer through the co-authorship of scientific articles increases the probability of firms owning a patent and the intensity of their innovation activity. Firms can take advantage of knowledge spillovers stemming from academia and, given the potentially large positive effects on public health, policymakers should incentivise such collaborations.

The second policy implication pertains to the interplay between collective and private incentives in fostering collaboration. Public sector scholars do not have institutional incentives to engage in co-publishing with colleagues from private firms. Given that academic careers and department evaluations for accessing public funding are mainly based on publication records, scholars may be willing to co-author papers with scientists from private companies, only if this increases the publishability of their research in highly impactful journals. Therefore, in this specific research field, policymakers should pursue a performance evaluation strategy at individual and institutional levels to align private and collective incentives, encouraging academic scholars to engage in joint publications with the private sector by rating these publications more highly.

Nevertheless, our findings regarding the presence of an "anticipatory effect" of co-publishing on innovation outcomes rule out the presence of 'defensive publication strategy' in biopharma industry and reveal the potential temporal misalignment of incentives in publication timing. Academics, driven by the increasing pressure to "publish or perish" enforced by university research evaluation policies, are motivated to publish their work quickly and preferably with high quality. In contrast, corporate scientists must align themselves with the needs of their company, prioritising the protection of research discoveries through patent filings and delaying the dissemination (and publication) of new knowledge. This misalignment in timing-based incentives may hinder collaborations and co-authorships among firm and university scientists, which have been shown to be advantageous for fostering innovation. As previously highlighted, both the issues have been central in the economics of science literature, investigating scientists' dual productivity in terms of both publishing and patenting. In order to take into account, the incentives of both—university scientists and firms—it is then crucial to establish a dedicated initiative that encourages such co-authorship in a highly relevant sector like biopharmaceuticals, relieving the pressure to publish quickly and instead rewarding the production of jointly authored publications that bridge the public-private divide.

Policymakers might have thus far overlooked the issue stemming from the structural and temporal misalignment of incentives between public and private scientists in biopharmaceutical research. The latter have, in fact, taken several actions, paying attention only to other technology transfer modes, such as spinoff creation. Finally, co-publishing is a knowledge cross-fertilisation tool that can also have positive effects on academic research. For this reason, universities might find it productive to promote collaboration between academics and researchers from the private sector to increase their research output and the number of highly ranked publications in their portfolios

Appendix

See Table 8.

Table 8 Robustness for the presence of excess of zeros

	Dependent variable: no. of patents							
	Panel a—Zero inflated negative binomial (ZINB)				Panel b—Pseudo poisson maximum likelihood (PPML)			
Main covariate:	No. of co-publications (ln)				No. of co-publications (ln)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Co-publications	0.033	−0.002	−0.018	−0.040	0.042**	0.014	−0.004	−0.002
	(0.031)	(0.027)	(0.026)	(0.029)	(0.019)	(0.018)	(0.018)	(0.019)
Co-publications (1-y fwd)		0.096***	0.080**	0.072*		0.059***	0.036*	0.004
		(0.036)	(0.034)	(0.038)		(0.022)	(0.021)	(0.023)
Co-publications (2-y fwd)			0.049*	0.007			0.060**	0.009
			(0.030)	(0.033)			(0.025)	(0.023)
Co-publications (3-y fwd)				0.093**				0.106***
				(0.037)				(0.026)
Previous collaborations (ln)	0.007	−0.035	−0.043	−0.052	0.014	−0.002	−0.005	−0.010
	(0.056)	(0.040)	(0.044)	(0.042)	(0.015)	(0.016)	(0.016)	(0.016)
Total publications (ln)	0.068***	0.062**	0.056**	0.058**	0.089***	0.084***	0.079***	0.079***
	(0.025)	(0.025)	(0.026)	(0.027)	(0.018)	(0.018)	(0.018)	(0.017)
R&D expenditure (ln)	−0.009	−0.010	−0.011	−0.011	0.001	0.000	−0.000	−0.003
	(0.009)	(0.009)	(0.009)	(0.009)	(0.006)	(0.006)	(0.005)	(0.006)
No. of employees (ln)	0.396***	0.376***	0.373**	0.334***	0.373***	0.374***	0.371***	0.366***
	(0.142)	(0.146)	(0.161)	(0.116)	(0.123)	(0.123)	(0.125)	(0.131)
Capital stock (ln)	−0.014	−0.004	−0.002	0.020	0.234***	0.221***	0.209***	0.187**
	(0.118)	(0.121)	(0.123)	(0.099)	(0.071)	(0.072)	(0.072)	(0.076)
Value-added (ln)	0.207*	0.215*	0.217*	0.220**	0.129	0.127	0.126	0.126
	(0.109)	(0.110)	(0.120)	(0.097)	(0.115)	(0.115)	(0.117)	(0.121)
Firm's age (ln)	−0.283	−0.338**	−0.351*	−0.342***	−0.302***	−0.297***	−0.305***	−0.309***
	(0.503)	(0.153)	(0.187)	(0.116)	(0.026)	(0.026)	(0.026)	(0.027)
Linear combination of leads			0.129***	**0.172*** **			0.096***	0.119***
			(0.047)	(0.053)			(0.029)	(0.025)
N	3000	3000	3000	3000	3348	3348	3346	3000
R^2					0.83	0.82	0.83	0.88
Year FE		Yes	Yes	Yes		Yes	Yes	Yes

Table 8 (continued)

	Dependent variable: no. of patents							
	Panel a—Zero inflated negative binomial (ZINB)				Panel b—Pseudo poisson maximum likelihood (PPML)			
Main covariate:	No. of co-publications (ln)				No. of co-publications (ln)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sector FE		Yes	Yes	Yes		Yes	Yes	Yes
Region FE		Yes	Yes	Yes		Yes	Yes	Yes

Firm-clustered standard errors in parentheses ***$p<$**$p<0.05$, *$p<0.1$. Inflate models for ZINB include, as determinants, the control variables adopted in the main text, our previous collaborations proxy and all the leads of the co-publishing variable

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