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NETWORKING AND CLUSTERING OF INNOVATIVE FIRMS :

Knowledge diffusion between large firms, SMEs and platforms, The case of patents in Artificial Intelligence

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TABLE OF CONTENTS

1. Introduction

Within the knowledge-based economies, the role of knowledge and innovation as drivers of growth are of critical importance. In the context of the new capitalism, where modern businesses have to face a number of new challenges such as digitization and knowledge-based economies, a prominent part is played by platforms. Taking advantage of the generative nature of digital, this emerging organisational models known – and supposed- to create value by favouring cooperation between different actors in the market and the way they are changing the diffusion of knowledge and the collaboration between firms are making platforms an engine of innovation (Gawer and Cusumano, 2007). At the same time, their implementation and management rely more and more on Artificial Intelligence (AI) technologies (Mucha and Seppala, 2020), making the two concepts – platforms and AI technologies – strongly interrelated and object of the interest of many researchers and practitioners, especially if we take into account the policy perspective in the European context (Bounfour, forthcoming).

The way knowledge is produced and diffuses between organisations is a phenomenon that has always attracted considerable interest among scholars. Many aspects are yet to be explored, especially with the advent of platforms and new technologies. Being knowledge by nature an elusive concept, the first issue is of course its measurement, a difficult task that scholars have faced so far using a variety of proxies, such as R&D investment and indicators based on patent publications. Another issue concerns how the knowledge created by countries, industries, firms, or other organisations diffuses and affects productivity of others, even when located far away from where the knowledge is originally produced. At the microeconomic level, the knowledge produced by large firms, SMEs and other public and private organisations is of course different and spreads in the production networks in different ways. Moreover, not every sector in the economy benefits of knowledge in the same way.

In this study, we bridge the above concepts and focus on the Artificial Intelligence (AI) sector and on knowledge diffusion via platforms. We concentrate the attention of the diffusion of knowledge between different types of organisations, distinguishing not only between platforms, large firms, SMEs and universities. To this end, we use patent-based data and analyse a panel of worldwide firms that share the characteristic of having collaborated with platforms at least once in their life. We do so in order to restrict the analysis to those applicants that have a certain degree of capability in producing knowledge. The underlying idea is that connectedness between firms is essential to generate spillovers, and collaborations are a good proxy for measuring this connectedness. In other words, we assume that those companies that collaborate with others are more able to produce knowledge that can be exploited by others. The analysis considers the period 1990-2020 and includes a panel of 234 applicants, divided by type. Using both patent applications and publications, we build indicators for knowledge flows, knowledge stocks and knowledge spillovers, and we evaluate the effect of the latter ones on knowledge creation via negative binomial panel regressions.

The study is structured as follows. Section 2 describes knowledge diffusion between large firms, SMEs and platforms, while section 3 concentrates more specifically on the literature that uses patents for studying knowledge spillovers. The data used in the empirical analysis are presented in section 4 while the methodological issues are discussed in section 5. Section 6 illustrates the results and section 6 concludes.

2. Knowledge diffusion between large firms, SMEs and platforms

Collaborating and innovating firms are those that are more likely to survive the market (Belitski, 2019). The benefits of collaborations have been emphasised by many in the literature (Cassiman and Veugelers, 2006; Fleming and Sorenson, 2004; Garriga et al., 2013). Knowledge spillovers, defined as exchanges of knowledge that do not imply a financial compensation, are the main means through which collaborations produce beneficial effects to firms. The benefits produced by these spillovers are generally uneven, as businesses of different size and organisational structure take advantage of the network of the exchanges in very different ways.

From the organisational point of view, a first distinction can be made between large firms and SMEs in the way they treat knowledge. Larger firms with considerable resources can deploy costly patent practices such as patent thickets in order to enhance the lock-in effect (Shapiro, 2000; Wang, 2007).

On the other hand, SMEs face resource constraints that limit their ability to benefit from their innovation through intellectual property strategies (Holgersson and Granstrand, 2017). Regarding to manufacturing, distribution, marketing and extended R&D funding, SMEs may lack resources and capabilities that are crucial for transforming inventions into production technologies. Under their scarce resources, small and medium-sized businesses must find ways to achieve manufacturing economies of scale, in order to successfully market their goods and to provide appropriate support services, and this allows them to work with other organisations. In new areas, SMEs are versatile and more creative, but may lack capital and capabilities. Large companies may be less flexible, but they tend to have better capacity to develop and/or introduce product or process innovations, and these resources act as complementary assets to lure SMEs to work collaboratively with them (Barney and Clark, 2007).

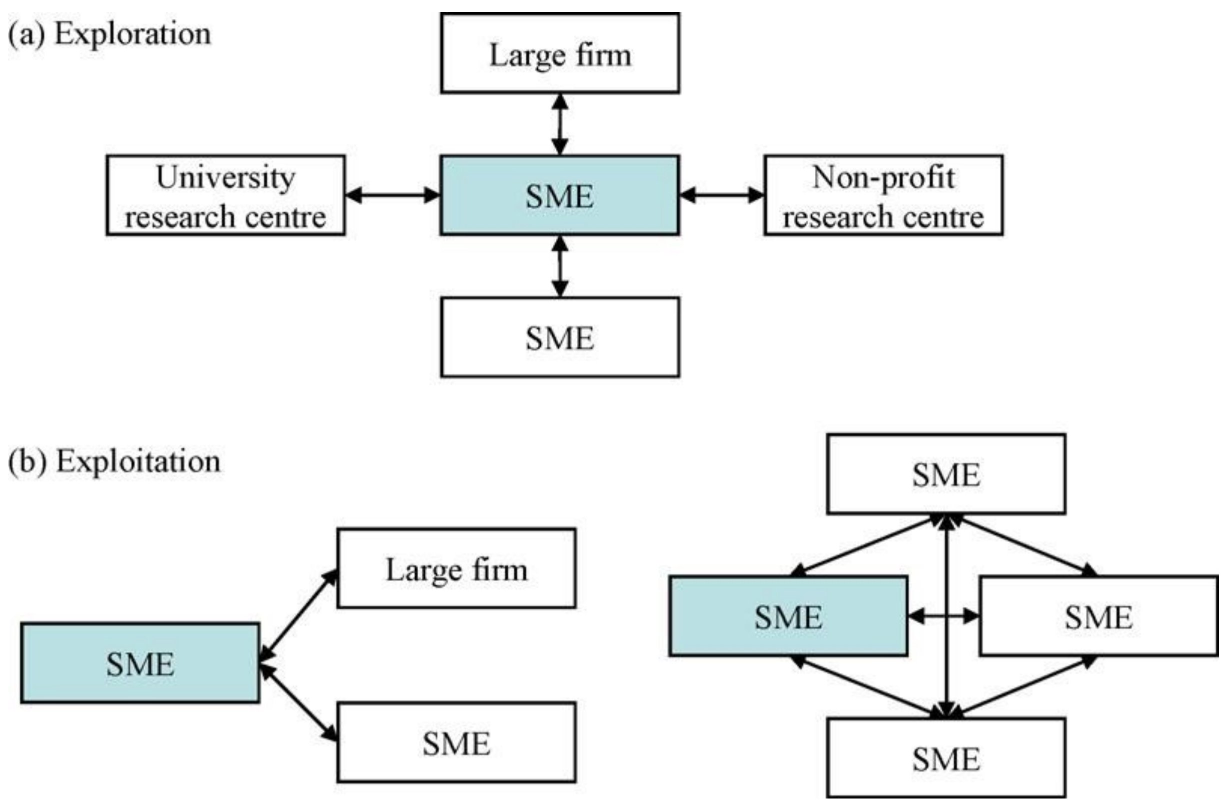
There are three key reasons for this. First, in the context of SMEs, collaborative work with large companies boosts the commercialisation of their products. Specifically, strategic alliances between SMEs and large companies are frequent in the biotechnology industry since R&D expenditure is high and SMEs have long commercialization cycles (Nestic et al., 2015; Shan et al., 1994). Second, through strategic R&D collaboration, each company obtains external information and knowledge resources (Laurie, 2002). Resource constraints restrict the capacity of SMEs to introduce new products and partnerships, illustrating why they have access to the necessary resources. Thirdly, collaborating with a SME from the viewpoint of a large company is a means of obtaining people who have the right combination of specialized skills to make new products (Sawers et al., 2008). Small firms also allow large firms to supervise the advancement of new technologies and equipment, since this innovation gap in product innovations is narrowed by collaborative SMEs (Nieto and Santamaría, 2010).

While partnerships with large firms have also helped small and medium-sized enterprises, they may often oblige SMEs to share their technical competence with large firms, resulting in greater versatility for large firms, thus negating a substantial competitive advantage for SMEs. As a consequence, as

SMEs acquire opportunities to partner for big corporations, they lose opportunities to compete with them (Narula, 2002). SMEs could also be needed to manufacture a cheap commodity that meets the lowest requirements of large corporations, thus slowing further innovation on the part of SMEs. An alternative model is a network that has been described as a particular form of relationship that links a series of individuals, objects or events (Nohria et al., 1992). Well-built and operated networks may give direct benefits to small and medium-sized businesses (Inkpen and Tsang, 2005), allowing them to decipher and assess relevant information flows, such as technological transition, sources of technical assistance, business needs and strategic choices by other enterprises, thus improving their competitive edge (Bougrain and Haudeville, 2002). In addition to successful co-development of innovative goods and services (Gulati, 1998), network members are influenced by the experience of each other, resulting in learning consequences for future innovation (Argote and Ingram, 2000). SMEs generally specialize in a particular area, and network participation can be an important means of effectively penetrating larger markets and gaining complementary capital and rising core competencies in order to increase their chances of engaging with their major rivals. The networking model of investing together to share risks and benefits will help SMEs grow more market opportunities, especially for start-ups.

Closer connections with larger firms can limit opportunities and alternatives for SMEs, and innovative SMEs are more likely to establish external networks with other SMEs or organisations, like universities and private research establishments (Rothwell, 1991), as shown in Figure 1. SMEs are more likely to use external collaborations at the exploration stage so that they can focus on sustaining high levels of internal expertise in a small range of technology fields (Narula, 2004). At the same time, they display a preference for partnering with public research organisations and universities due to the extreme fear of providing competitors with their technology (Tidd and Trewhella, 1997). SMEs aim to build value at the exploitation level by entering into supplier-customer partnerships with big corporations (Luukkonen, 2005), outsourcing deals or strategic alliances with other SMEs. There is a rich literature on partner preference, partnership mechanisms, and the benefits and drawbacks of each form of collaboration, most of which deals with bi-lateral partnerships (Vanhaverbeke and Cloodt, 2005).

Figure 1. SMEs open innovation.



Source: Lee et al. (2010)

In this context, the advent of platforms adds a further level of analysis. These are in fact large companies, but that do not follow the traditional production chain of "ordinary" companies. Platforms are characterised by a high capability of connecting people, companies, technologies and resources, and are able to create value out of these connections (Täuscher and Laudien, 2018). They can profit from the network systems they create not only because they facilitate exchanges, but also because they can exploit strong economies of scales and use technologies to reduce marginal costs. Therefore, platforms not only should be differentiated from large firms, but also should be considered as central hubs where knowledge is created.

In these circumstances, a central role is played by digital technologies. In fact, in order to develop their networks, platforms are both major developers and final users of new technologies (Mucha and Seppala, 2020). Among these technologies, a prominent role is played by AI technologies, as stated also by Jeff Bezos (2017) in his letter to the shareholders, where he stressed that AI is not only delivery drones, Amazon go or Alexa, but much happens “beneath the surface”. He mentioned algorithms for “demand forecasting, product search ranking, product and deals recommendations, merchandising placements, fraud detection, translations, and much more” (Bezos, 2017). In general, there is a strong correlation between the success of a platform in reaching a high number of users and the use of AI technologies. This phenomenon has been remarked by many in the literature as what is commonly referred as the virtuous cycle of AI (Lee et al., 2019), in which the availability of AI technologies allows platforms to obtain more users, that in turn allow the to obtain more technologies and data and therefore again more users and so on.

For all these reasons, the AI sector plays a prominent role in the transmission of knowledge spillovers. Platforms are the main developers of these technologies, and they should be put at the centre of any analysis that attempts to evaluate the advantages of these technologies. Moreover, a wide spectrum of actors benefits from the externalities generated by the technology created by them. In the remainder of this study, we attempt to bridge these elements in a consistent way to shed light on the mechanisms that drive the transmission of knowledge and on the firm categories that take advantage from it.

3. Patents and technological diffusion

In the literature that investigates innovation diffusion and collaborating network of firms, two main trends can be identified: the first attempts to visualize and map collaboration networks by means of co-citation clustering and patent bibliometrics techniques, while the second relies on patent data to examine the diffusion of knowledge between firms. Examples of the former are (2011), who present an overview of the evolution of patent co-citation network-based technology structure, and Wang et al. (2013), who, via co-citation cluster analysis, develop a model of knowledge-transfer analysis that allows them to map knowledge sources and technology fronts. A more econometric example is provided by MingJi and Ping (2014), who perform an empirical analysis in the nanobiopharmaceutical field of university-industry patent innovation collaboration. In addition to previously published literature in university-industry partnership, they suggest that small-world systems have a parabolic effect on patent innovation.

Our study relates more to the second strand of literature mentioned, which uses the number of citations and published patents to examine knowledge diffusion between firms. However, most of the works in this literature focus on knowledge diffusion between countries, regions or industries, while little research investigating the innovation diffusion between companies of different size or different typology. Some exceptions are Globerman et al. (2000), who, using references in Swedish patent data, explore technology sourcing in Swedish multi-national enterprises (MNEs) and nonmultinational SMEs. Their findings suggest that trade contacts are essential for the acquisition of technology in SMEs, while they are less important in MNEs. Via a Bayesian network model, Lee et al. (2016) suggest a new partner selection method when a large organization evaluates SMEs as potential candidates for R&D collaboration. The paper points out a structured and analytical approach that can help forming successful relationships between large corporations and SMEs. Chen et al. (2018) explore instead the impact of technical diversity, information flow and capability on the success of industrial innovation. Information flow and knowledge capacity are found to be negatively moderating the effects of technical diversity on the performance of industrial innovation. Finally, the work that is closer to ours is the one of Kim et al. (2014), who distinguish between large firms and

SMEs in a panel of Korean firms and study patent-based spillover effects on both knowledge creation and productivity growth. In a similar fashion, we use patents, co-patent and citations to explore knowledge creation in the AI sector between different types of businesses.

4. Data

We extracted data from the Derwent World Patent Index database, which offers enhanced patent data including disambiguated assignee identification which significantly contributes to improve our analysis at applicant scale. We collected data by employing the definition of AI patents resulting from the WIPO Technology Trends report on AI (WIPO, 2019). This comprehensive request designed by AI experts combines keywords associated with technological classifications and remains to our knowledge the best definition of AI patents. After extraction, this dataset is composed of 516 770 INPADOC families. Among those, we selected patents of 27 major platforms worldwide [1] in this dataset and identified 207 applicants which applied at least for one patent in collaboration with one of those platforms. All AI patents from those platforms' collaborators were then added to the platform dataset. Overall, the dataset includes 75 061 INPADOC families. Selecting platforms and their collaborators allows us to build a dataset composed of firms producing technologies of higher compatibility and consequently more likely to benefit each other through spillovers. In addition, using data extracted from Orbis and completed by hand, doing so makes it possible to classify applicants in this sample as either platforms (27), large firms (96), SMEs (85) or universities (26), and analyze spillover effects between those categories.

Table 1. Descriptive analysis of the dataset

		Applications	Average forward citations per patent	Collaborative Patents
University	10%	7539	6,37	13%
Large Firms	45%	34511	15,06	6%
Platform	42%	31638	15,76	4%
SME	3%	2543	28,64	17%

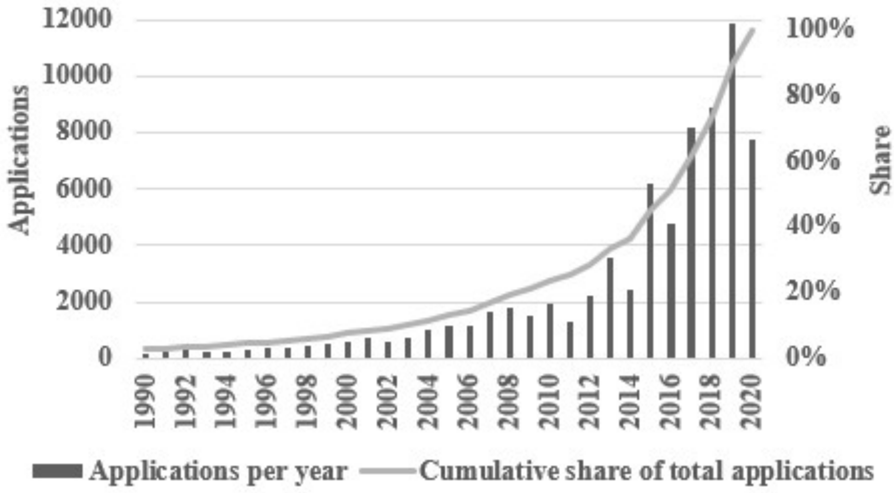
[1] The names of the platforms in the sample are listed in Appendix A.

Platforms and large firms AI portfolios are very similar and reflect patent practices of large firms. As expected, they applied for a considerably large number of patents and combinedly represent 87% of the dataset. On average, their patents receive a similar number of forward citations from latter patents.

Compared to SMEs patents which receive, on average, nearly twice this number, platforms and large firms' patents seem to be of lower quality. Their portfolios are composed of high-quality patents protecting core technologies and defensive patents receiving a low number of citations which constitute patent thickets. On the other hand, SME, which do not possess resources to apply for numerous patents, focus their strategies around a few high-quality patents. In a consistent way, the share of collaborative patents (more than one assignee for the patent) is much lower for large firms and platforms, which reflects their appropriation strategies. University patents appear to be the less cited ones, which reflect previous results on academics versus non-academics patents and their average lower value (Lissoni and Montobbio, 2015).

Patent applications per year are extremely low before 1990 and only represent 3% of the dataset over 70 years, as shown in Figure 2. This is the reason why we restrict the analysis to the post-1990 period. Moreover, due to the 18-month patent examination, we decided to truncate our sample for the year 2020. Consequently, our dataset is windowed between 1990 and 2019 and includes 65 419 INPADOC Families.

Figure 2. Application per year and cumulative share of total applications over time

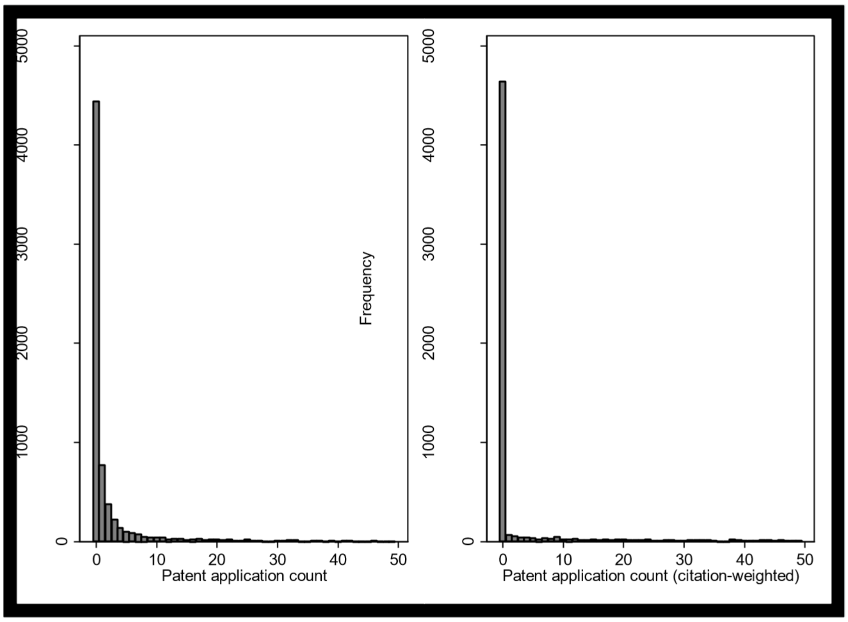


After restricting the analysis to those applicants that collaborated at least once with platforms, the final panel includes 234 applicants, observed for the period 1990-2019. For each applicant, we collect information on the total new patent applications and publications in each period, using both the simple count of patents and a count weighted by the number of citations. Then, we compute the stock of patents of each applicant as cumulative sum of their published patents from the early 1900, and the spillover measures with the method we explain in the next section. The descriptive statistics of the all variables used are presented in Table 2. In Figure 3, we show instead the frequency of the two main patent application variables: patent application count (left) and patent application citation weighted count (right). All variables are count variables with a high presence of zeroes and with a standard deviation much higher than their mean, indicating the presence of over dispersion in the data.

Table 2. Descriptive statistics

	observations	mean	St. deviation	min	max
Patent application count	7020	9.474929	55.87053	0	1298
Patent application count (citation-weighted)	7020	158.6917	751.9135	0	19071
Patent publication count	7020	7.039886	46.60358	0	1588
Patent publication count (citation-weighted)	7020	155.0466	718.4262	0	14631
Patent application count - stock	7020	70.08832	342.4955	0	8985
Patent application count (citation-weighted) - stock	7020	2314.993	10123.9	0	161139
Patent publication count - stock	7020	46.67678	235.9122	0	6105
Patent publication count (citation-weighted) - stock	7020	1644.122	7928.969	0	157037

Figure 3. Patent count frequency histograms



Note. Observations greater than 50 have been cut to ease visualization

5. The model

5.1 Spillover definition

Following Jaffe (1986), we measure spillovers using technological distance between applicants. Spillovers are computed as the sum of published patents by other firms, in which each firm's patents in the summation is weighted by a term that represents technological proximity with the firm that receives the spillover. In other words, the spillover term for each firm *i* at time *t* is the sum of all patents published by all the other firms:

$$Spillover_{it} = \sum_{i \neq j} m_{ij} P_{jt}^{p} \tag{1}$$

Where P_{jt}^{p} is the stock of published patents by firm *j* until time *t* , while the weight term m_{ij} represents the technological proximity between firms *i* and *j*, measured as in Jaffe (1986). Defining *K* technological classes, the technological proximity between firm *i* and *j* is:

$$\sum_{k=1}^{K} P_{ik}^{p} \, P_{jk}^{p} \tag{2}$$

$$m_{ij}\frac{}{\sqrt{\sum_{k=1}^{K}(P_{ik}^{\mathrm{p}})^2\sum_{k=1}^{K}(P_{jk}^{\mathrm{p}})^2}}$$

Where $P_{ik}^{p}$is the total stock of published patents[2] by firm i in category k and P_{jk}^{p} the total stock of published patents by firm j in category k. To compute the *NxN* matrix of technological proximity coefficients, we consider the 9 AI categories reported in Table 4.

Table 4. AI technological categories

	AI technological category
1	Computer vision
2	Control methods
3	Distributed artificial intelligence
4	Knowledge representation and reasoning
5	Natural language processing
6	Planning and scheduling
7	Predictive analytics
8	Robotics
9	Speech processing

5.2 Econometric specification

The main objective of the study is to assess the impact of patent-based knowledge spillovers on knowledge creation in the AI sector. To this end, a panel of 234 worldwide firms that collaborated at least once with platforms is used. The econometric model we estimate is the following:[3]

$$\Delta P_{ita} = \beta_0 + \beta_1 \Delta P_{it-1} + \beta_2 P_{itp} + \beta_3 Spillover_{it-1} \tag{3}$$

[2] The stock of patents of each firms are computed as cumulative sum of all patents published by each firm from the early 1900 to 2020. We use the total stock of patents rather than new patents published as more representative of the technological category of a firm. In fact, there are many SMEs in our sample that in many years did not publish any patents, for which it would be difficult to identify the category if we used new patents published in each year.

[3] Given the difficulty of pairing non-harmonised firm names with other databases, we follow Kim et al. (2014) in ignoring possible controls variables and focusing on average relationships. We assume that the effect of controls is captured by the constant terms.

Where i and t denote firm and time period, P^a patent application count and P^p published patent count. Therefore, we hypothesize that new knowledge created by firm i at time t depends on its own stock of knowledge and on spillovers of knowledge coming from other firms. The choice of one lag for the dependent variables reflects the assumption that it takes one year for knowledge to be absorbed and reflected in new patent applications. Moreover, for robustness, we also specify the model using citation-weighted measures of patent applications and publications, rather than the simple count.[4]

We are also able to distinguish spillovers by type of applicant, identifying four categories: platforms, large companies, SMEs and universities. In formulas, equation (3) can be rewritten as:

$$\beta_0 + \beta_1 \Delta P_{it-1} + \beta_2 P_{it}^{p} + \beta_3 Spillover_{it-1}^{p} + \beta_4 Spillover_{it-1}^{l} + \beta_5 Spillover_{it-1}^{s} + \beta_6 Spillover_{it-1}^{u} \quad (4)$$

Where the notations p, l, s and u denote respectively platforms, large companies, SMEs and universities. Therefore, for each type of applicant, the spillover is computed as the (weighted) sum of all patents published by all the organisations belonging to that category in that specific year. Moreover, equation (4) is estimated in four subsamples - one for each of the four categories - in order to assess the effect of each type of spillover on the knowledge creation of each category in turn.

The model is estimated via negative binomial regressions that, among the models advised for count data, is the one that suits better the characteristics of our data, which are, as shown in the data section, highly skewed and over dispersed.

6. Results

The output of the estimation of equation (3) equation (4) and is reported in Table 5. All models are estimated with the negative binomial regression method. In particular, in columns (1) – (5) the variable used are based on the simple count of patents, while in columns (6) – (10), for robustness,

[4] In this case, also the Jaffe matrix of coefficients is re-computed using citation weighted measures rather than the simple count.

the same models are estimated using patent count weighted with citations. For simplicity, spillover coefficients appear in the same rows even if their computation in columns (1) – (5) and (6) – (10) differs. Single categories' spillovers have been included in separate regressions to avoid multicollinearity, as all spillover terms are highly correlated, as shown in Table 6.

The coefficient of the overall spillovers measure is positive and significant in both models (specifications 1 and 5), indicating a positive spillover effect on knowledge creation. In the remaining specifications, also the effect of large firms, SMEs and platforms' spillovers is positive, regardless of the dependent variable and method of count used.

Table 5. Main analysis results.

Dependent variable:	patent application count					patent application weighted citations count				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Patent application count (lag)	0.263*** (15.02)	0.272*** (15.45)	0.265*** (14.85)	0.268*** (15.32)	0.266*** (15.17)					
Patent publication stock	-0.0271*** (-3.66)	-0.0323*** (-4.53)	-0.0296*** (-3.97)	-0.0285*** (-3.98)	-0.0289*** (-3.98)					
Patent application weighted count (lag)						0.0250*** (24.11)	0.0251*** (24.18)	0.0251*** (24.13)	0.0250*** (24.04)	0.0250*** (24.05)
Patent publication stock (weighted count)						0.00137*** (9.88)	0.00138*** (9.89)	0.00137*** (9.85)	0.00137*** (9.83)	0.00137*** (9.79)
Overall spillover	0.00329*** (3.75)					0.0000632*** (3.03)				
Spillover (SMEs)		0.0385*** (3.01)					0.000725*** (2.63)			
Spillover (large)			0.00458*** (2.89)					0.000106** (2.53)		
Spillover (universities)				0.0736*** (4.72)					0.00131** (2.49)	
Spillover (platforms)					0.00686*** (3.68)					0.000125*** (2.98)
Constant	-1.970*** (-10.94)	-1.944*** (-10.81)	-1.969*** (-10.92)	-1.939*** (-10.78)	-1.953*** (-10.86)	-3.556*** (-19.12)	-3.554*** (-19.11)	-3.555*** (-19.12)	-3.556*** (-19.12)	-3.552*** (-19.10)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ln (r)	-0.336*** (-3.84)	-0.337*** (-3.84)	-0.338*** (-3.85)	-0.335*** (-3.82)	-0.337*** (-3.84)	-1.144*** (-13.69)	-1.143*** (-13.67)	-1.143*** (-13.67)	-1.144*** (-13.68)	-1.144*** (-13.68)
ln (s)	-0.444*** (-4.95)	-0.448*** (-5.00)	-0.447*** (-4.99)	-0.445*** (-4.97)	-0.446*** (-4.98)	1.701*** (8.68)	1.705*** (8.69)	1.704*** (8.69)	1.702*** (8.68)	1.702*** (8.68)
Observations	6786	6786	6786	6786	6786	6786	6786	6786	6786	6786
Chi-squared	2951.2	2928.3	2931.9	2968.8	2940.3	1646.5	1642.6	1643.1	1643.6	1643.9
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Log-likelihood	-10029.9	-10032.6	-10032.9	-10025.6	-10030.2	-18819.4	-18820.6	-18820.9	-18821.0	-18819.6

Notes: ***, **, and * indicate significance at 1, 5, and 10 percent, respectively. t statistics are reported in parentheses. The dependent variable is patent application count in columns (1) - (5) and patent application weighted citations count in (6) - (10). Spillovers are computed using stock of published patents, using patent count in columns (1) - (5) and patent citation weighted count (6) - (10). All explanatory variables are considered in their first lag. All explanatory variables' coefficients have been multiplied by 100 to ease readability. Chi-squared statistics and relative P-value show the significance of the models and compares it to a Poisson specification. In the negative binomial specifications, ln (r) and ln (s) are over-dispersion parameters.

It is interesting also to compare spillover elasticities. In the negative binomial model, coefficients can be directly interpreted as elasticities, even if data were not log transformed before the estimation.

However, for the sake of readability, all explanatory variables' coefficients have been multiplied by 100, so that elasticities can be obtained dividing back by 100. Interestingly, Universities spillovers are those that have a bigger effect, followed by SMEs, while large firms and platforms spillovers have smaller coefficient magnitude. Results are also consistent when using the weighted count method rather than the simple count.

Table 6. Spillover correlations

	SMEs	Large	Platforms	Universities
SMEs	1			
Large firms	0.8175	1		
Platforms	0.6681	0.9503	1	
Universities	0.7012	0.9575	0.9755	1

We now look at the effect of the single spillovers on singles categories of applicants. These are shown in Tables 7 to 10, which show, respectively, the effect of spillovers on large firms, SMEs, platforms and Universities. As before, in each table the first five columns refer to the models estimated using the simple patent count, while the last five use citation-weighted patent count. Large firms, shown in Table 7, are those that benefit from a wider range of spillovers, being all significant and positive, regardless of the source and the computation method used. Interestingly, the magnitude of the overall spillover coefficient is also rather similar to that of SMEs, shown in Table 8, even though when using citations, the latter ones are not significant. This may indicate that unlike large firms, SMEs seem to benefit from all publications, when large firms exclusively benefit from notable inventions. In Table 8, SMEs knowledge creation benefits of spillovers from large firms, platforms and universities, but do not benefit of their own spillover, suggesting that their technological survey is restricted to large players. The strongest effect comes from Universities, probably because of the higher bargaining power that SMEs have with Universities with respect to the other categories but also because universities are by nature producers of knowledge. The closer position of SMEs with Universities is also testified also by the fact that SMEs patents are in general cited more by academic organisations. This can be seen as some kind of spinoff effect, as for example many SMEs are often founded by professors or academic researchers. However, significance changes when using citations, but not the relative importance: SMEs spillovers are still the less important, being even significantly negative.

In Table 9 we show the Universities subsample. Here, Universities are not much affected by spillovers, at least when using the simple count. A significant positive overall effect is instead found when weighting the measures with citations, which is something understandable being citations more frequent among academicians. In general, it is also reasonable that universities do not get much knowledge from other categories, being their knowledge produced internally and exchange mostly with other academic organisations. This is line with what found by others in the literature (Breschi and Lissoni, 2001; Wennberg et al., 2011), who highlight that most of the knowledge created by universities is transmitted indirectly by people that start businesses after studying.

Finally, in Table 10 the platforms' subsample is shown. Interestingly, knowledge creation of platforms does not benefit from spillovers as the overall spillover, measured with the simple patent count even significantly negative. This effect seems to come from large firms, whose spillovers' coefficient is significantly negative too, while all the others are non-significant. When using citation based measures those negative effects vanish, but still none of the spillovers is significantly positive. We can explain this with the fact that platforms invest much internally, internalise much their knowledge and are ahead of the curve in terms of technology. They contribute considerably to the system in terms of knowledge but without absorbing as much from others. There may be also a knowledge leakage effect, of which large firm may benefit particularly, having the right organisation to do so. In fact, it seems reasonable that most of the knowledge platforms use is created internally, while the knowledge they obtain indirectly is negligible in comparison.

Table 7. Regressions in the large firms subsample

Dependent variable:	patent application count					patent application weighted citations count				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Patent application count (lag)	0.489*** (11.92)	0.483*** (11.44)	0.505*** (12.49)	0.487*** (11.40)	0.478*** (11.32)					
Patent publication stock	-0.0648*** (-4.93)	-0.0702*** (-5.29)	-0.0660*** (-5.15)	-0.0676*** (-5.06)	-0.0690*** (-5.11)					
Patent application weighted count (lag)						0.0298*** (13.53)	0.0298*** (13.59)	0.0300*** (13.65)	0.0300*** (13.61)	0.0299*** (13.50)
Patent publication stock (weighted count)						0.00262*** (7.25)	0.00266*** (7.37)	0.00260*** (7.21)	0.00255*** (7.11)	0.00252*** (7.12)
Overall spillover	0.00471*** (3.90)					0.0000770** (2.44)				
Spillover (SMEs)		0.0513*** (2.78)					0.00119*** (2.84)			
Spillover (large)			0.00918*** (4.19)					0.000137** (2.19)		
Spillover (universities)				0.0894*** (4.22)					0.00150* (1.91)	
Spillover (platforms)					0.00671*** (2.60)					0.000125** (2.05)
Constant	-1.647*** (-7.00)	-1.615*** (-6.87)	-1.663*** (-7.06)	-1.605*** (-6.83)	-1.620*** (-6.89)	-3.211*** (-13.23)	-3.212*** (-13.23)	-3.212*** (-13.23)	-3.211*** (-13.22)	-3.205*** (-13.20)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ln (r)	-0.273** (-2.03)	-0.280** (-2.08)	-0.270** (-2.01)	-0.275** (-2.05)	-0.282** (-2.10)	-1.105*** (-7.76)	-1.102*** (-7.71)	-1.106*** (-7.76)	-1.109*** (-7.80)	-1.110*** (-7.82)
ln (s)	-0.152 (-1.05)	-0.157 (-1.08)	-0.151 (-1.05)	-0.156 (-1.08)	-0.162 (-1.12)	2.197*** (6.02)	2.209*** (6.03)	2.196*** (6.02)	2.182*** (6.00)	2.178*** (5.99)
Observations	2775	2775	2775	2775	2775	2775	2775	2775	2775	2775
Chi-squared	1477.5	1453.3	1494.5	1477.3	1446.1	752.6	757.0	751.9	749.5	750.0
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Log-likelihood	-4894.2	-4898.2	-4893.1	-4892.9	-4898.7	-9184.4	-9183.3	-9185.0	-9185.6	-9185.3

Notes: ***, **, and * indicate significance at 1, 5, and 10 percent, respectively. t statistics are reported in parentheses. The dependent variable is patent application count in columns (1) - (5) and patent application weighted citations count in (6) - (10). Spillovers are computed using stock of published patents, using patent count in columns (1) - (5) and patent citation weighted count (6) - (10). All explanatory variables are considered in their first lag. All explanatory variables' coefficients have been multiplied by 100 to ease readability. Chi-squared statistics and relative P-value show the significance of the models and compares it to a Poisson specification. In the negative binomial specifications, ln (r) and ln (s) are over-dispersion parameters.

Table 8. Regressions in the SMEs subsample

Dependent variable:	patent application count					patent application weighted citations count				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Patent application count (lag)	3.840*** (7.50)	3.970*** (7.76)	3.862*** (7.56)	4.002*** (8.20)	3.868*** (7.53)					
Patent publication stock	0.0388 (0.47)	0.0778 (0.95)	0.0475 (0.58)	-0.0137 (-0.16)	0.0500 (0.60)					
Patent application weighted count (lag)						0.133*** (14.24)	0.135*** (14.38)	0.116*** (11.09)	0.115*** (11.08)	0.132*** (14.27)
Patent publication stock (weighted count)						0.0360*** (20.61)	0.0366*** (20.83)	0.0330*** (14.88)	0.0326*** (14.67)	0.0357*** (20.58)
Overall spillover	0.00482* (1.85)					-0.0000422 (-0.93)				
Spillover (SMEs)		0.0186 (0.56)					-0.00107* (-1.79)			
Spillover (large)			0.00804* (1.70)					-0.0000958 (-0.96)		
Spillover (universities)				0.161*** (3.17)					-0.000473 (-0.37)	
Spillover (platforms)					0.00966* (1.65)					-0.0000977 (-1.02)
Constant	-2.142*** (-4.23)	-2.109*** (-4.17)	-2.157*** (-4.26)	-2.076*** (-4.10)	-2.117*** (-4.19)	-5.098*** (-9.13)	-4.491*** (-10.86)	-4.638*** (-9.25)	-4.642*** (-9.26)	-5.865*** (-7.17)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ln (r)	0.647*** (3.72)	0.654*** (3.76)	0.647*** (3.71)	0.655*** (3.75)	0.652*** (3.74)	7.571*** (65.32)	12.02*** (103.94)	-0.251 (-1.07)	-0.259 (-1.11)	13.48*** (115.69)
ln (s)	-0.281* (-1.76)	-0.259 (-1.61)	-0.276* (-1.72)	-0.302* (-1.90)	-0.276* (-1.72)	14.08 (.)	18.52 (.)	4.164*** (7.86)	4.141*** (7.85)	22.98 (.)
Observations	2436	2436	2436	2436	2436	2436	2436	2436	2436	2436
Chi-squared	318.9	312.1	317.4	329.4	317.3	989.9	995.4	521.6	521.4	979.4
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Log-likelihood	-1721.9	-1723.6	-1722.2	-1717.9	-1722.3	-3418.5	-3417.1	-3401.0	-3401.3	-3420.7

Notes: ***, **, and * indicate significance at 1, 5, and 10 percent, respectively. t statistics are reported in parentheses. The dependent variable is patent application count in columns (1) - (5) and patent application weighted citations count in (6) - (10). Spillovers are computed using stock of published patents, using patent count in columns (1) - (5) and patent citation weighted count (6) - (10). All explanatory variables are considered in their first lag. All explanatory variables' coefficients have been multiplied by 100 to ease readability. Chi-squared statistics and relative P-value show the significance of the models and compares it to a Poisson specification. In the negative binomial specifications, ln (r) and ln (s) are over-dispersion parameters.

Table 9. Regressions in the universities subsample

Dependent variable:	patent application count					patent application weighted citations count				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Patent application count (lag)	1.487*** (7.26)	1.497*** (7.31)	1.494*** (7.28)	1.500*** (7.33)	1.487*** (7.25)					
Patent publication stock	-0.240** (-2.38)	-0.250** (-2.51)	-0.243** (-2.40)	-0.250** (-2.50)	-0.246** (-2.45)					
Patent application weighted count (lag)						0.546*** (10.17)	0.794*** (6.28)	0.784*** (6.16)	0.784*** (6.16)	0.788*** (6.26)
Patent publication stock (weighted count)						-0.00562 (-0.94)	0.0649*** (3.56)	0.0652*** (3.56)	0.0650*** (3.54)	0.0648*** (3.54)
Overall spillover	-0.00203 (-1.49)					0.00353*** (9.18)				
Spillover (SMEs)		-0.0289 (-1.19)					0.00169 (1.18)			
Spillover (large)			-0.00445* (-1.76)					0.000111 (0.51)		
Spillover (universities)				-0.0279 (-0.98)					0.00140 (0.53)	
Spillover (platforms)					-0.00277 (-0.93)					0.000201 (0.91)
Constant	-1.302*** (-3.16)	-1.319*** (-3.20)	-1.285*** (-3.11)	-1.326*** (-3.22)	-1.324*** (-3.21)	-29.18 (-0.00)	-0.293 (-0.30)	0.180 (0.19)	0.143 (0.14)	-0.144 (-0.14)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ln (r)	0.164 (0.61)	0.159 (0.59)	0.166 (0.61)	0.160 (0.59)	0.160 (0.59)	-8.524*** (-6.45)				
ln (s)	0.0809 (0.30)	0.0772 (0.28)	0.0798 (0.29)	0.0816 (0.30)	0.0853 (0.31)	12.00 (.)				
ln (alpha)							2.023*** (32.63)	2.025*** (32.67)	2.025*** (32.67)	2.024*** (32.65)
Observations	754	754	754	754	754	754	754	754	754	754
Chi-squared	1371.3	1362.4	1378.3	1359.7	1355.5	.	80.44	80.74	80.70	80.58
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Log-likelihood	-1230.9	-1231.3	-1230.5	-1231.5	-1231.5	-7246.5	-2585.1	-2585.6	-2585.6	-2585.4

Notes: ***, **, and * indicate significance at 1, 5, and 10 percent, respectively. t statistics are reported in parentheses. The dependent variable is patent application count in columns (1) - (5) and patent application weighted citations count in (6) - (10). Spillovers are computed using stock of published patents, using patent count in columns (1) - (5) and patent citation weighted count (6) - (10). All explanatory variables are considered in their first lag. All explanatory variables' coefficients have been multiplied by 100 to ease readability. Chi-squared statistics and relative P-value show the significance of the models and compares it to a Poisson specification. In the negative binomial specifications, ln (r) and ln (s) are over-dispersion parameters.

Table 10. Regressions in the platforms subsample

Dependent variable:	patent application count					patent application weighted citations count				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Patent application count (lag)	0.284*** (9.55)	0.273*** (9.59)	0.290*** (9.80)	0.272*** (9.70)	0.273*** (9.61)					
Patent publication stock	-0.0758*** (-5.03)	-0.0698*** (-4.74)	-0.0775*** (-5.35)	-0.0688*** (-4.77)	-0.0688*** (-4.66)					
Patent application weighted count (lag)						0.0224*** (12.39)	0.0224*** (12.37)	0.0224*** (12.39)	0.0223*** (12.40)	0.0224*** (12.38)
Patent publication stock (weighted count)						0.000170 (0.76)	0.000155 (0.69)	0.000170 (0.77)	0.000183 (0.83)	0.000165 (0.74)
Overall spillover	-0.00365** (-2.09)					0.0000308 (0.62)				
Spillover (SMEs)		-0.0338 (-1.24)					-0.000124 (-0.19)			
Spillover (large)			-0.00901*** (-2.79)					0.0000671 (0.69)		
Spillover (universities)				-0.0378 (-1.16)					0.00156 (1.26)	
Spillover (platforms)					-0.00334 (-0.90)					0.0000447 (0.46)
Constant	-2.800*** (-4.84)	-2.826*** (-4.89)	-2.776*** (-4.80)	-2.837*** (-4.91)	-2.828*** (-4.89)	-3.826*** (-6.62)	-3.820*** (-6.61)	-3.827*** (-6.63)	-3.833*** (-6.64)	-3.824*** (-6.62)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ln (r)	-0.832*** (-3.61)	-0.830*** (-3.60)	-0.833*** (-3.61)	-0.829*** (-3.60)	-0.828*** (-3.59)	-1.404*** (-6.38)	-1.408*** (-6.40)	-1.403*** (-6.38)	-1.401*** (-6.38)	-1.405*** (-6.39)
ln (s)	-0.346 (-1.23)	-0.336 (-1.19)	-0.350 (-1.25)	-0.331 (-1.17)	-0.333 (-1.18)	1.144** (2.22)	1.125** (2.18)	1.146** (2.22)	1.152** (2.24)	1.137** (2.21)
Observations	821	821	821	821	821	821	821	821	821	821
Chi-squared	1057.8	1051.8	1064.4	1052.0	1052.1	489.7	488.5	490.0	493.2	489.2
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Log-likelihood	-1934.7	-1935.9	-1933.1	-1936.0	-1936.3	-3338.7	-3338.9	-3338.6	-3338.1	-3338.8

Notes: ***, **, and * indicate significance at 1, 5, and 10 percent, respectively. t statistics are reported in parentheses. The dependent variable is patent application count in columns (1) - (5) and patent application weighted citations count in (6) - (10). Spillovers are computed using stock of published patents, using patent count in columns (1) - (5) and patent citation weighted count (6) - (10). All explanatory variables are considered in their first lag. All explanatory variables' coefficients have been multiplied by 100 to ease readability. Chi-squared statistics and relative P-value show the significance of the models and compares it to a Poisson specification. In the negative binomial specifications, ln (r) and ln (s) are over-dispersion parameters.

7. Conclusion

In this study, the phenomenon of knowledge creation in the artificial intelligence (AI) sector have been analysed. Because of the central role played by platforms in the development of new technologies such as AI, we concentrate our attention on applicants that collaborate with platforms, considering that collaborations create an essential link for the transmission of knowledge. Using patent data and a panel of 27 major platforms and 207 worldwide applicants that share the characteristics of having collaborated at least once with platforms in their life, indicators of knowledge creation, knowledge stock and knowledge spillovers are constructed. Distinguishing applicants by organisations type (platforms, large firms, SMEs and universities), the effect of different types of spillovers on each of the different categories' knowledge is studied via negative binomial regressions. We found evidence in favour of knowledge diffusion between firms in the whole sample, with important differences among categories. From one side, all types of spillovers (stemming from each category) are found to affect the overall knowledge creation in the sample. On the other hand, not every category benefits from these spillovers: large firms are found to be those that benefit more and from a greater number of spillovers, followed by SMEs, which take advantage of all types of spillovers but those produced by SMEs themselves. Instead, Universities receive very little benefits from spillovers in terms of knowledge creation, as most of the knowledge they create is transmitted internally. Interestingly, also platforms, despite being the main creators of knowledge in the AI sector, do not benefit of spillovers. They produce more knowledge internally than that they capture from other categories, as they mostly internalise their knowledge and what they obtain from others is compensated by some kind of leakage effect, with other companies that take advantage of the technologies they create.

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Appendix A. List of platforms

Table A1. List of platforms

Platform	Patent families
IBM	5989
Microsoft	4079
Baidu	3535
Tencent Holdings	3433
Google	2663
Intel	1751
Alibaba Group	1525
Amazon	1122
Apple	957
Facebook	440
Oracle	398
Uber	174
eBay	157
Salesforce	140
Rakuten	123
PayPal	95
Twitter	44
Linkedin	31
Netflix	23
JD.com	19
Square, Inc.	11
Workday	7