Louvain School of Management
and University of Cologne

Knowledge spillovers from artificial intelligence faculty:
The impact of universities on regional innovation ecosystems

Author:
Clara Friederieke Jacobi

Master's thesis with the view of getting the degrees:
Master in Management, Corporate Development +
Master in Business Engineering, Innovation Management

Supervisors:
Benoît Gailly
Prof. Dr. Christian Schwens
Dr. Tim Haarhaus

Academic Year 2023-2024

Table of Content

List of Tables

List of Figures

List of Abbreviations

AI	Artificial intelligence
AIPD	Artificial Intelligence Patent Dataset
CSRankings	Computer Science Rankings
IT	Information technology
R&D	Research and development
US	United States
USPTO	United States Patent and Trademark Office
VIF	Variance inflation factor
WIPO	World Intellectual Property Organization

1 Introduction

AI is the new electricity. It has the potential to transform every industry and to create huge economic value. […] If governments, universities and corporations work together to encourage education and innovation, then all nations and all people have an almost unlimited opportunity to be part of this new AI economy.

(A. Ng, 2018, cited by Jewell, 2019)

In recent years, artificial intelligence (AI) has received increasing attention from both media and the research community. Continuous innovation has led to significant improvements in this technology (D. Ng, Leung, Chu, & Qiao, 2021). Although there is no universally accepted definition, AI is generally described as "advanced technologies that exhibit human-like intelligence" (Lazzeretti, Domenech, Hervas-Oliver, & Innocenti, 2023, p. 1297). It is predicted that AI will not only transform the field of computer science, but the entire economy and society (J. Xu & Babaian, 2021). Universities have played a central role in the preliminary developments of AI and continue to contribute to the discovery of new knowledge (Jiang, X. Li, Luo, S. Yin, & Kaynak 2022; C. Zhang & Lu, 2021). Simultaneously, companies have increasingly adopted AI technologies, recognizing their strategic importance in improving performance and remaining competitive (Lazzeretti et al., 2023). With the majority of AI patents coming from the private sector, companies are also the main drivers of innovation in this field (World Intellectual Property Organization [WIPO], 2019). Recognizing universities as knowledge creators and private companies as primary innovators emphasizes the importance of studying the relationships and knowledge flows between these actors. Therefore, AI innovation is often considered within the framework of innovation ecosystems, defined as "interdependent networks of actors with the functional goal of enabling value creation [...] through innovation and technology development" (Sultana, Turkina, & Cohendet, 2023, p. 11). In this context, AI faculties are emphasized as important connectors between academia and the private sector (Gofman & Jin, 2024).

Previous research has examined different factors that affect the formation of innovation ecosystems. Sectoral (e.g., Autio, Nambisan, Thomas, & Wright, 2018; Beltagui, Rosli, & Candi, 2020) and geographical proximity (e.g., Heaton, Siegel, & Teece, 2019; Simmie, 2002; Varga, 2000) can promote synergies and coordination between actors. The emergence of AI innovation ecosystems is often considered from a bottom-up perspective (Sultana et al., 2023), which focuses on the influence of different actors within the ecosystem (e.g., Cooke, Uranga, & Etxebarria, 1997; Igna & Venturini, 2023; Van Looy et al., 2011). Among these, universities are highlighted as key contributors. They conduct basic research (e.g., Cowan & Zinovyeva, 2013; Etzkowitz & Leyesdorff, 2000; Heaton et al., 2019), with faculty taking a central role (Kenney & Patton, 2009; Zucker, Darby, & Armstrong, 2002). Beyond that, they initiate knowledge flows within regions (e.g., Heaton et al., 2019; G. Xu, Wu, Minshall, & Zhou, 2018). These flows can take the form of intentional, compensated knowledge transfers (e.g., Agrawal, 2001; Bozeman & Gaughan, 2007; Kenney & Patton, 2009). Furthermore, knowledge spillovers, defined as "unintentional knowledge flows from one network party to another" (Ko & G. Liu, 2015, p. 263), have been increasingly studied due to their impact on growth (e.g., Agarwal, Audretsch, & Sarkar, 2010; Audretsch & Keilbach, 2008; Audretsch & Lehmann, 2005) and innovativeness (e.g., Akcigit, Hanley, & Serrano-Velarde, 2020; Bottazzi & Peri, 2003; Igna & Venturini, 2023) of firms and regions. Knowledge spillovers are enabled by different mechanisms depending on the type of knowledge. Codified, explicit knowledge can be easily shared, while tacit, intuitive knowledge is tied to individuals, making it more difficult to disseminate (e.g., Audretsch, Lehmann, & Warning, 2005; Belenzon & Schankerman, 2013; Bottazzi & Peri, 2003; Callon, 1994). The latter is often associated with new, specific AI knowledge (Igna & Venturini, 2023). It needs to be actively mobilized by knowledge owners (Ko & G. Liu, 2015), acting as "knowledge spillover agents" (Bergman & Schubert, 2005, p. 171). In the context of universities, this role has been studied for graduates (e.g., Audretsch & Lehmann, 2005;

Leten, Landoni, & Van Looy, 2014; Toivanen & Väänänen, 2016), academic staff (e.g., Andersson, Quigley, & Wilhelmsson, 2009; Van Looy et al., 2011) and faculties (e.g., Cowan & Zinovyeva, 2013; Gofman & Jin, 2024). Researchers have also explored the temporal dimension of knowledge spillovers to accumulate and be translated into innovation (e.g., Cowan & Zinovyeva, 2013; Valero & Van Reenen, 2019). Additionally, several potential factors have been identified that may moderate the intensity of knowledge spillovers between universities and industry. First, personal interactions can be enhanced by facilities for physical long-term (e.g., Bednář, Danko, & Smékalová, 2021; Buzard, Carlino, Hunt, Carr, & Smith, 2020) and short-term proximity, with a focus on conferences in the field of AI (e.g., Chai & Freeman, 2019; Cantú-Ortiz, 2014). Second, at the university level, scholars have discussed the availability of financial resources (e.g., Audretsch & Feldman, 1996; Cowan & Zinovyeva, 2013; Varga, 2000) and intermediary institutions (e.g., Gál & Ptáček, 2011; Meléndez, Fuster, Lockett, & Del-Águila-Obra, 2020). Third, at the industry level, spillovers can be influenced by factors such as the demand for (e.g., Igna & Venturini, 2023; Varga, 2000) and openness to external knowledge (Bergman & Schubert, 2005), as well as the ability to absorb this knowledge (e.g., Harris & Yan, 2018; Keller, 1996; Veugelers, 1997).

The existing literature provides an opportunity to contribute to the understanding of AI education, innovation ecosystems, and knowledge spillovers. First, it is necessary to determine the precise role of faculty in innovation ecosystems and knowledge spillover processes. Previous studies have examined the overall impact of universities (e.g., Etzkowitz & Leyesdorff, 2000; Heaton et al., 2019; G. Xu et al., 2018) and specific internal actors (e.g., Andersson et al., 2009; Cowan & Zinovyeva, 2013; Leten et al., 2014). Despite their importance in knowledge production and innovation, research on faculties as a source of spillovers is limited. Scholars have focused on their influence on startup creation (Gofman & Jin, 2024; Wang & K. Huang, 2021). However, this provides a limited perspective on private sector innovation as a whole.

Furthermore, the impact of faculty knowledge was considered in a codified form, such as publications, and in specific regional and sectoral contexts (Cowan & Zinovyeva, 2013; Zucker et al., 2002). Given that AI has unique research needs due to its technological characteristics (Igna & Venturini, 2023) and future relevance (Gofman & Jin, 2024), few conclusions can be drawn regarding spillovers in this domain. The second gap therefore relates to AI innovation ecosystems, which have received limited attention in the literature. Previous research has mainly focused on the impact of AI technologies on the overall innovation activities of firms and regions (e.g., Bessen, Impink, Reichensperger, & Seamans, 2022; C. Li et al., 2023; K. Yin, Cai, & C. Huang, 2022), without addressing innovation within the AI domain itself. Furthermore, the impact of AI education on innovation has been little studied (Gofman & Jin, 2024; J. Xu & Babaian, 2021). Therefore, it is necessary to identify knowledge spillovers from faculties to industry within AI innovation ecosystems. In this context, it needs to be validated whether potential moderating effects on knowledge spillovers hold under these conditions. When examining time, existing research typically considers lags of one to five years (e.g., Valero & Van Reenen, 2019; Varga, Anselin, & Ács, 2005), neglecting the exploration of larger time dimensions or a comparative analysis to determine when spillovers are most present.

The objective of this study is to investigate the impact of AI faculties on the innovation of private firms in regional ecosystems. Based on the existing literature on AI education, innovation ecosystems and knowledge spillovers, the main hypothesis is that AI faculties can enhance the innovativeness of private firms in regions. Faculty members are considered significant knowledge producers. Since AI knowledge is mainly tacit, professors further act as knowledge spillover agents for its diffusion. Spillover channels are assumed to be both direct, such as personal interactions within networks developed over time (e.g., Balconi & Laboranti, 2006), and indirect, such as through the education of students entering the industry (e.g., Mansfield, 1995). Second, the present study suggests that the effects become more apparent over time through the process of sharing and adapting knowledge, and transforming it into innovation and patents (e.g., Ács, Anselin, & Varga, 2002; Cowan & Zinovyeva, 2013). Third, several contextual conditions are considered as potential moderators that may influence the relationship between faculty and private AI innovation. By creating proximity, the presence of AI conferences in a region may increase spillovers as a venue for personal interaction (e.g., Chai & Freeman, 2019). At the university level, external investment in university research and development (R&D) can be leveraged for knowledge production and diffusion (e.g., Varga et al., 2005). Finally, an increase in the availability of human capital in the information technology (IT) sector may lead to a higher demand for AI knowledge in the industry and improve firms' ability to utilize external knowledge (e.g., Igna & Venturini, 2023). Hypotheses were tested based on a sample of 1,140 counties in the United States (US) over the period 2000 to 2020. The measure of innovation was the number of patents granted to private firms (e.g., Cowan & Zinovyeva, 2013; Igna & Venturini, 2023), considering only those related to AI. The dataset was constructed using patent information from the United States Patent and Trademark Office (USPTO), merged with information on AI faculties from the Computer Science Rankings (CSRankings) database. The study employed a random effects panel regression with standard errors clustered at the county level. Additionally, a marginal effects approach was used to investigate potential moderating effects.

This study contributes to the existing literature on AI education, innovation ecosystems and knowledge spillovers in several ways. First, it identifies the significant impact of AI faculty on the generation of AI innovation by private firms. This provides a more nuanced view of the importance of universities in the development of innovation ecosystems (e.g., Heaton et al., 2019) and emphasizes the specific role of professors within these networks. The focus on AI brings clarity to the largely unexplored area of AI innovation ecosystems and demonstrates the impact of AI education on the private sector (e.g., Gofman & Jin, 2024; Sultana et al., 2023). Second, the study improves the understanding of knowledge spillovers by incorporating a temporal dimension and showing that spillovers peak after about seven years. This finding can be attributed to the specific conditions of the AI technology, the underlying knowledge, and the patenting process. Third, the study presents a more detailed perspective on knowledge spillover channels. The relevance of faculty involvement, observed at the regional level, emphasizes the value of personal interactions over passive activities such as university patenting (Igna & Venturini, 2023). These results are supported by the findings on potential moderators of the impact of AI faculty on private innovation. The results for both AI conferences and investment in university R&D are not significant, indicating that simply providing opportunities for knowledge production and diffusion is not, in itself, sufficient. Rather, these channels need to be leveraged through active engagement and strategic resource allocation (e.g., Audretsch, 2012; Zucker et al., 2002). The significant moderating effect of human capital in the IT sector underlines the importance of qualified spillover agents on the demand side. However, the effect is significant only at high levels, reflecting the increased requirements of AI innovation for surplus human resources and skills. The findings also have several practical implications. Policy makers and universities are encouraged to strategically allocate resources, taking into account faculty development and intermediary institutions within regions. Additionally, they should support collaborative research platforms and projects to increase exchange with the private sector. In turn, companies should actively engage with academia to benefit from external knowledge, influence the research agenda, and consider spillover opportunities in location decisions.

The study is structured as follows: Following the introduction, Chapter 2 provides an overview of the current research on AI, innovation ecosystems, and knowledge spillovers. Chapter 3 develops the hypotheses, while Chapter 4 outlines the data collection approach and the empirical framework. Chapter 5 presents the empirical results, which are further discussed in Chapter 6, including their practical implications, study limitations, and recommendations for future research. Finally, Chapter 7 summarizes the main findings of the study.

2 Theoretical background

2.1 Artificial intelligence

The term 'artificial intelligence' was first introduced in 1956 by the computer scientist John McCarthy during a conference at Dartmouth College in the US. Since then, various definitions have emerged (N. Liu, Shapira, & Yue, 2021; Zawacki-Richter, Marín, Bond, & Gouverneur, 2019). McCarthy himself defines AI as "the science and technology of making intelligent machines" (Stanford University, 2022a, p. 1). AI serves as a surrogate and facilitator of human behavior, enabling "computational artifacts to perform tasks that otherwise would require human intelligence" (Taddeo & Floridi, 2018, p. 751). As a "general-purpose technology" (Stanford University, 2019, p. 91), AI is used as an umbrella term for different technological approaches and methods such as 'machine learning', 'expert systems', 'pattern recognition', 'decision support systems', 'natural language processing', and 'problem solving' (C. Zhang & Lu, 2021; Jiang et al., 2022). Machine learning is considered the dominant technology, present in one-third of all patented AI innovations (WIPO, 2019). Another distinction is based on the extent to which human intelligence can be simulated. 'Weak AI' refers to systems designed for limited, predefined tasks based on objective factors, such as mapping applications or automated hotlines. 'Strong AI' incorporates subjective factors and human experience for more complex tasks, including decision making (Zawacki-Richter et al., 2019; Jiang et al., 2022).

Particularly since the late 1980s, as computing power and data availability have increased, there has been significant progress in both the theoretical research on, and practical applications of, AI. It has become a focus of interest for companies, governments, and academic institutions (Jiang et al., 2022). Advances in AI technology are driven by corporate investment in R&D and venture capital (WIPO, 2019). According to a McKinsey study (2021), 56% of organizations have already adopted AI in at least one business area. Governments have also recognized the importance of the topic and are shaping its progress through public funding and national policies

(N. Liu et al., 2021, C. Zhang & Lu, 2021). Apart from the US with its 'National AI R&D Strategic Plan', most developed countries have implemented national AI strategies (Organization for Economic Cooperation and Development, 2021). The importance of AI has led to increased investment in academic research by both private and public actors, for example through the funding of faculties engaged in AI R&D (US Executive Office, 2019; WIPO, 2019).

Universities have played an important role in the development of AI technologies from the very beginning. They were responsible for the introduction of the concept and the development of the first expert system at Stanford University (Jiang et al., 2022). Subsequently, AI has gained prominence in academia, leading to an exponential growth in research and publication activity over the last two decades (N. Liu et al., 2021). Predominantly located in computer science and IT departments, AI faculties and courses have increasingly been established in academic curricula in non-technical fields such as business (J. Xu & Babaian, 2021), healthcare, and medicine (A. Sapci & H. Sapci, 2020). However, there is limited literature on AI education (J. Xu & Babaian, 2021). Most studies focus on the use of AI as a pedagogical tool to improve the educational experience and success (e.g., Shum & Luckin, 2019; Zawacki-Richter et al., 2019). Other research strands investigate design principles for AI curricula (e.g., Langley, 2019; Nguyen, Tuunanen, Gardner, & Sheridan, 2020), the integration of AI courses into other programs (e.g., J. Xu & Babaian, 2021), and implementation challenges related to the breadth and dynamics of the knowledge base, the lack of teaching expertise, and substitutes such as online courses and forums (e.g., Langley, 2019; J. Xu & Babaian, 2021). Despite this, the impact of AI research and education from universities remains poorly understood. Gofman and Jin (2024) and Wang and K. Huang (2021) emphasize the importance of AI education for entrepreneurial activity, finding a positive impact on the creation of AI startups by graduates. However, most studies focus on the impact of education in technological fields rather than AI specifically (e.g., Audretsch & Lehmann, 2005; Leten et al., 2014; Toivanen & Väänänen, 2016).

2.2 Innovation ecosystems

2.2.1 Concept of innovation ecosystems

The significant improvements in AI technologies have been enabled by continuous innovation in this field (D. Ng et al., 2021). Innovation is defined as “the introduction of a new product or service, or a new way to create value for customers by introducing a new or changing an existing business model” (Yaghmaie & Vanhaverbeke, 2020, p. 284). In the context of increasing technological and project complexity, modern innovations often require interaction with various types of organizations that go beyond bilateral engagements between firms (Yaghmaie & Vanhaverbeke, 2020). Therefore, scholars have developed theories to explain the ability to generate innovations within regional networks (Autio, et al., 2018). The concept of ‘innovation ecosystems’ is based on the related notion of ‘business ecosystems’ by Moore (1993) and has gained relevance among scholars in recent years (e.g., Sultana et al., 2023; Van Looy et al., 2011; G. Xu et al., 2018). In the literature, innovation ecosystems are also referred to as ‘innovation clusters’, ‘innovation milieus’, or ‘regional innovation systems’ (Autio et al., 2018). To date, no single definition has been reached (Yaghmaie & Vanhaverbeke, 2020). Innovation ecosystems are typically described as networks of interdependent actors involved in the dynamic process of generating innovation and developing technology (Sultana et al., 2023; G. Xu et al., 2018).

Previous research has identified several characteristics and mechanisms that are central to the emergence of innovation ecosystems. First, ecosystems require sectoral proximity, as they focus on interactions between organizations in a particular technology, a particular industry, or several related industries. They enable coordination and knowledge sharing among stakeholders, thereby allowing for the maximization of benefits from corresponding technologies (Autio et al., 2018; Sultana et al., 2023). Thereby, they facilitate radical innovations and are particularly relevant in emerging digital sectors (Beltagiu et al., 2020), such as AI (Lazzeretti et al., 2023;

Sultana et al., 2023). Second, the importance of geographical proximity in the formation of innovation ecosystems has been highlighted. Geographical proximity reduces transaction and logistical costs, facilitates coordination among actors, and enables a more efficient utilization of valuable resources (Autio et al., 2018; Simmie, 2002). However, innovation ecosystems are not limited to a particular geographic scale. Scholars have noted that they exist at national, local and even intra-organizational levels (Heaton et al., 2019). Furthermore, the literature explains the emergence of innovation ecosystems from two different perspectives, namely top-down and bottom-up (Sultana et al., 2023). The top-down approach describes their development through regulatory contexts (Davies, Flanagan, Bolton, Roderick, & Joyce, 2020), such as policies, intellectual property rights, taxes (Cooke et al., 1997; Van Looy et al., 2011), and public funding (H. Sun, Edziah, C. Sun, & Kporsu, 2019). On the other hand, the bottom-up approach is based on the common goals and innovation efforts of actors within the ecosystem (Sultana et al., 2023), such as R&D activities (Van Looy et al., 2011), internal culture and training (Cooke et al., 1997), and collaboration (Davies et al., 2020).

To categorize the actors involved in the formation of innovation ecosystems, scholars distinguish between passive supporters, such as policymakers and financial organizations, and active participants, such as firms, universities, and research centers (X. Li, 2009; Panetti, Parmentola, Ferretti, & Reynolds, 2019). Moreover, the 'triple helix' model proposed by Etzkowitz and Leyesdorff (2000), which identifies industry, government, and universities as central actors, has been widely adopted in the literature (e.g., Davies et al., 2020; G. Xu et al., 2018). In this context, the influence of universities on regional innovation ecosystems has received increasing attention (Cowan & Zinovyeva, 2013). Universities are often referred to as "anchor players" (G. Xu et al., 2018, p. 218) and "central to the growth or decline of their ecosystems" (Heaton et al., 2019, p. 923). Scholars have found that they attract firms, investment, and human capital (Etzkowitz & Leyesdorff, 2000) while also providing a foundation for economic development (e.g., Audretsch & Lehmann, 2005; Valero & Van Reenen, 2019) and innovative activity (e.g., Simmie, 2002; Cowan & Zinovyeva, 2013). The role of universities is particularly pronounced in innovation ecosystems related to emerging technologies, which are highly dependent on scientific research (G. Xu et al., 2018). Therefore, studying the influence of universities on innovation ecosystems is particularly important in the context of AI.

2.2.2 Artificial intelligence innovation ecosystems

The existing literature primarily focuses on the impact of AI technologies on the overall innovative activity of firms (e.g., Bessen et al., 2022; C. Li et al., 2023) and regions (e.g., Lazzeretti et al., 2023; K. Yin et al., 2022). Less emphasis is placed on innovation within the AI domain itself. Studies on AI innovation ecosystems explain their emergence based on both top-down and bottom-up elements (Sultana et al., 2023). The top-down perspective considers the influence of data regulation and availability (Bessen et al., 2022), AI strategies, and government funding (Jiang et al., 2022; Sultana et al., 2023). On the other hand, bottom-up elements are present in firms' internal R&D efforts (Igna & Venturini, 2023; Jee & S. Sohn, 2023), the demand for new knowledge (Igna & Venturini, 2023), the willingness to share knowledge, and the presence of intermediaries between organizations (Sultana et al., 2023). Despite their critical role, there are noticeable research gaps on AI innovation ecosystems. Specifically, the actors who conduct research and innovate in this field have hardly been studied (Igna & Venturini, 2023). Existing studies mainly focus on relationships within the private sector (e.g., Igna & Venturini, 2023; Jee & S. Sohn, 2023). The impact of universities on AI innovation is often analyzed from a historical perspective (Jiang et al., 2022; C. Zhang & Lu, 2021) or through case studies (Doloreux & Turkina, 2021; Sultana et al., 2023). Quantitative studies tend to focus only on specific aspects of the ecosystem, such as the influence of universities on the creation of AI startups (e.g., Gofman & Jin, 2024). These approaches make it difficult to apply the findings to a broader, future scope.

2.3 Knowledge spillovers

2.3.1 Knowledge spillovers in innovation ecosystems

Knowledge is a crucial source of competitive advantage for firms (Audretsch & Lehmann, 2005). Given that it reduces the uncertainty associated with innovation, it is particularly important for innovative firms (Alexy, George, & Salter, 2013; Simmie, 2002). Within networks, actors can draw on multiple sources to acquire external knowledge. On the one hand, knowledge transfers describe intentional knowledge flows that require collaboration and often involve compensation (Ko & G. Liu, 2015). They can be achieved through mechanisms such as licensing (Kenney & Patton, 2009; Thompson, Ziedonis, & Mowery, 2018), joint ventures (Agrawal, 2001) or contract research (Bozeman & Gaughan, 2007). On the other hand, knowledge spillovers represent unintended, less formalized knowledge flows (Ko & G. Liu, 2015). They are also referred to as positive externalities of knowledge (Audretsch & Lehmann, 2005; Autio et al., 2018). At the microeconomic level, knowledge spillovers have been found to have a positive effect on the creation (Audretsch & Lehmann, 2005; Agarwal et al., 2010; Gofman & Jin, 2024), performance (Bloom, Schankerman, & Van Reenen, 2013), and innovative activity (Akcigit et al., 2020; Igna & Venturini, 2023) of firms. From a macroeconomic perspective, the impact of spillovers extends to entire regions in terms of economic growth (Audretsch & Keilbach, 2008) and innovative activity (Simmie, 2002; Bottazzi & Peri, 2003). Therefore, the theory of knowledge spillovers has received increasing attention in research on regional innovation ecosystems (e.g., Davies et al., 2020; Jaffe, 1989; G. Xu et al., 2018).

Previous literature has identified different mechanisms of knowledge spillovers depending on the type of knowledge involved, distinguishing between explicit and tacit knowledge. Explicit knowledge is codified, easy to verbalize, and can be disseminated through channels such as publications, journals or codes (Audretsch & Lehmann, 2005). In contrast, tacit knowledge is intuitive, tied to individuals, and based on experience, know-how, and skills (Callon, 1994).

Many knowledge-intensive industries such as computers and software, and especially AI, depend heavily on new, tacit knowledge (Audretsch & Feldman, 1996; Igna & Venturini, 2023). Because it is based on individuals, the diffusion of tacit knowledge within and between organizations requires the active mobilization of knowledge owners (Ko & G. Liu, 2015), also referred to as "knowledge spillover agents" (Bergman & Schubert, 2005, p. 171). This includes mechanisms such as personal interactions, communication (Audretsch et al., 2005), social networks (Bottazzi & Peri, 2003), and human capital mobility (Döring & Schnellenbach, 2006). Moreover, tacit knowledge is geographically linked to its source (Belenzon & Schankerman, 2013). Thus, spatial proximity increases the impact of spillovers on innovation by reducing the costs of knowledge search, diffusion, and adoption (Audretsch & Lehmann, 2005). Scholars have considered the influence of spillovers on innovative activity at different regional scales, ranging from distances of five (Andersson et al., 2009) to 300 km (Bottazzi & Peri, 2003), and from the international (e.g., Valero & Van Reenen, 2019) to the national level, including federal states (e.g., Audretsch & Feldman, 1996) and counties (e.g., Ács et al., 2002). In addition, previous research has examined different time frames required for these mechanisms to accumulate, predominantly assuming lags of one (e.g., Igna & Venturini, 2023; C. Li et al., 2023), three (e.g., Varga et al., 2005), and five years (e.g., Cowan & Zinovyeva, 2013; Valero & Van Reenen, 2019).

Another strand of research focuses on the organizational actors involved in knowledge spillovers. Spillovers can occur in two directions: horizontally between competitors or between academic institutions (Gupta, 2008; Jee & S. Sohn, 2023), or vertically along the knowledge value chain, involving different types of organizations such as firms, universities, research centers, and consumers (Autio et al., 2018). Given their central role in regional innovation ecosystems (Etzkowitz & Leyesdorff, 2000), the importance of universities has also been recognized in the context of knowledge spillovers, particularly in high-technology sectors (Varga, 2000).

Griliches (1979) and Jaffe (1989) were among the first to study the impact of university spillovers on regional innovation. Researchers have identified various influencing factors, including the presence of a university (Cowan & Zinovyeva, 2013; Valero & Van Reenen, 2019), its ranking (Belenzon & Schankerman, 2013), and the number of publications (Van Looy et al., 2011). The literature has also considered the importance of knowledge spillover agents in a university context (Zucker et al., 2002). It has highlighted the role of graduates transitioning from academia to industry (Audretsch et al., 2005; Audretsch & Lehmann, 2005; Leten et al., 2014; Toivanen & Väänänen, 2016) and academic personnel (Andersson et al., 2009; Schiller & Diez, 2010; Van Looy et al., 2011). However, the literature on faculties as knowledge spillover agents is limited. While Power and Malmberg (2008) and Gofman and Jin (2024) examined the role of professors in educating students, they did not consider other spillover channels such as personal networks to industry. Cowan and Zinovyeva (2013) and Zucker et al. (2002) found positive effects of faculty on private innovation, as measured by patents. However, both papers only considered the diffusion of knowledge through codified channels, i.e., publications published by professors. However, knowledge related to AI technologies is often tacit and intangible, which poses challenges for its diffusion (Igna & Venturini, 2023). Additionally, the first paper focuses exclusively on Italy, while the second focuses on the biotechnology sector between 1976 and 1991. As many important AI innovations have occurred only in recent years and are highly dependent on regional policies (Jiang et al., 2022), limited conclusions can be drawn from these results. This emphasizes the need for a better understanding of spillovers in AI.

Nevertheless, the literature on knowledge spillovers in AI innovation ecosystems is also limited (Igna & Venturini, 2023). The determinants of spillovers have been studied at different levels. Spillovers between companies are found to be influenced by firm-internal factors such as technological maturity, degree of specialization, patent portfolio (Igna & Venturini, 2023), and AI-related publications (Jee & S. Sohn, 2023). Studies show mixed results regarding spillovers from universities to the private sector. Igna and Venturini (2023) investigate the impact of knowledge spillovers from AI patents issued by universities. They find no significant effect on innovation by private firms within regions. In contrast, Wang and K. Huang (2021) examine the impact of publications and graduates in different AI subfields. Gofman and Jin (2024) identify spillovers from AI professors as a relevant source of knowledge. Both papers report a positive impact of universities on the creation of AI startups. However, they do not consider innovation by all private firms. As the private sector accounts for the largest share of AI innovation (WIPO, 2019), further research is needed to determine the precise direction of spillovers from universities to private firms.

2.3.2 Moderating factors of knowledge spillovers from universities

Researchers have identified several factors that influence knowledge spillovers from universities to the private sector. These factors are related to the establishment of proximity between the two actors, as well as to levers at each level. First, the creation of physical proximity can enhance knowledge spillovers (Heaton et al., 2019). For long-term exchanges, studies have examined the positive effects of university campuses with laboratories for collaborative research (Buzard et al., 2020) or office facilities for startups (Bednář et al., 2021). For short-term exchanges, representatives from industry and academia can be brought together in the context of events, workshops or expert presentations (Belenzon & Schankerman, 2013; Cowan & Zinovyeva 2013). In particular, conferences are highlighted as facilitators of regional knowledge production and dissemination (Henderson & Burford, 2019), also in the context of AI technologies (Cantú-Ortiz, 2014). They enable spillovers through face-to-face communication (Chai & Freeman, 2019; Heaton et al., 2019) and the accumulation of expertise (Chai & Freeman, 2019), and stimulate further knowledge and innovation production (Audretsch & Belitski, 2021; Henderson & Burford, 2019; Kyvik & Larsen, 1994). Nevertheless, scholars have found that the intensity of spillovers at conferences varies depending on the subfield of AI (Wang & K.

Huang, 2021), the media used for knowledge presentation (De Simone et al., 2001; Rowe & Ilic, 2009), and the seniority (Chai & Freeman, 2019) as well as the location of researchers (Kyvik & Larsen, 1994).

At the university level, previous literature has emphasized the importance of intermediary institutions in reducing the gap between academia and industry, thereby facilitating knowledge spillovers (Gál & Ptáček, 2011; Meléndez et al., 2020). Additionally, research has shown that investment in university R&D has a positive impact on knowledge spillovers (e.g., Varga et al., 2005; Cowan & Zinovyeva, 2013). The availability of financial resources enables the increased production of valuable knowledge (Ács, Braunerhjelm, Audretsch, & Carlsson, 2008; Coe & Helpman, 1995), its dissemination through codification (Cohendet & Meyer-Krahmer, 2001; Zucker et al., 2002), and greater flexibility in terms of time and finances that can be allocated to spillover processes (Balconi & Laboranti, 2006). However, according to Akcigit et al. (2020), these resources alone are not a sufficient condition for knowledge spillovers. Rather, their effect depends on the type of research invested in, distinguishing between basic and applied research.

At the sectoral level, human capital in the IT industry serves as a moderator of the spillover effect (Nie, Gong, Zhao, Lai, & Chang, 2022). Human capital is defined as the "aggregate of individual knowledge, skills, and abilities" (Ployhart, Weekley, & Ramsey, 2009, p. 996). In the high-technology industry, IT professionals are found to positively influence knowledge spillovers in the local industry (Igna & Venturini, 2023; Varga, 2000). The presence of human capital suggests a larger ecosystem size (Operti & Carnabuci, 2014), which in turn implies a higher demand for external knowledge (Schiller & Diez, 2010; Varga, 2000) and increased competitive pressure to innovate (Bertschek, 1995). When considering individual firms within a sector, other factors can increase the effects of knowledge spillovers. Human capital has been used as an indicator of absorptive capacity in the context of spillovers (e.g., Harris & Yan, 2018; Keller, 1996; Veugelers, 1997). Absorptive capacity reflects the "ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends" (Cohen & Levinthal, 1990, p. 128). IT professionals facilitate the absorption and internal diffusion of knowledge as demand-side spillover agents (Bergman & Schubert, 2005; Harris & Yan, 2018). However, scholars note that other firm-level factors, such as high knowledge search costs (Zucker et al., 2002), high technological maturity of firms (Igna & Venturini, 2023), and a lack of openness to external knowledge (Bergman & Schubert, 2005), can weaken knowledge spillover effects.

3 Hypotheses development

3.1 Main effect

AI faculties contribute to the development of AI innovation with a dual role as knowledge creators and disseminators. Overall, universities are crucial sources of knowledge generation (Davies et al., 2020) and have been responsible for significant advancements in AI (Jiang et al., 2022). Professors, as central actors in the early stages of knowledge discovery, contribute significantly to these developments (Kenney & Patton, 2009; Zucker et al., 2002). Newly generated knowledge is often tacit, especially in the case of AI. Therefore, it is initially embodied by the researchers involved in the discoveries (Igna & Venturini, 2023; Zucker et al., 2002). In addition to their role in knowledge creation, universities facilitate the diffusion of knowledge between public and private entities (Doloreux & Turkina, 2021; Heaton et al., 2019). This is particularly relevant for technology-intensive knowledge (X. Li, 2009), which is related to the exploration of disruptive and high-technology innovations (Varga, 2000; G. Xu et al., 2018). As the majority of innovations in AI are generated by private firms (WIPO, 2019), knowledge spillovers from universities to the private sector seem essential for the development of AI innovation ecosystems. Professors can act as relevant agents in the generation of these innovations (Balconi & Laboranti, 2006; Kenney & Patton, 2009; Zucker et al., 2002) by facilitating the diffusion of tacit knowledge through several mechanisms.

First, faculties influence the industrial sector through personal interaction and contacts (Simmie, 2002). Their broad personal networks enable knowledge spillovers, as they often extend beyond academia into the private sector (Balconi & Laboranti, 2006; Varga, 2000). Professors' networks are based on a variety of sources through engagement with different teams and stakeholders in the industry over time. These include collaborative research projects with companies (Balconi & Laboranti, 2006; Schiller & Diez, 2010), participation in targeted research consortia (Berman, 1990), attendance at conferences and workshops (Chai & Freeman, 2019), and activities as consultants to industry (Mansfield, 1995; Varga, 1998). In addition, professors establish contacts by proactively approaching industry representatives. This engagement may involve seeking sponsorship and support for research projects or recruiting private sector professionals as guest speakers for lectures (Balconi & Laboranti, 2006; Berman, 1990). Finally, professors train a steady stream of students who often become industrial researchers after graduation, fostering long-term relationships between graduates and professors. Private interactions between faculties and former students can create an ongoing knowledge spillover even after graduation (Balconi & Laboranti, 2006). These interactions lead to numerous relationships with individual actors in the ecosystem. As a result, university knowledge can be more easily disseminated, sometimes even before formal publication (Simmie, 2002).

The second mechanism is the spillover of tacit knowledge through education. AI professors can share tacit knowledge directly with industry by offering workshops in private companies or by making seminars accessible to non-academic participants (Cowan & Zinovyeva, 2013). Additionally, tacit knowledge can be disseminated indirectly through graduates, who transfer their embodied knowledge to the employing firm after graduation (Mansfield, 1995). Particularly in high-technology fields such as AI, graduates play a crucial role in disseminating knowledge from academia to industry (Gofman & Jin, 2024).

These mechanisms of knowledge spillovers in AI are enhanced when regional proximity is taken into account (Simmie, 2002). Tacit knowledge is complex, intuitive, and regionally bound to its source. Proximity facilitates the direct interactions necessary for knowledge sharing and reduces the transaction costs of this process (Audretsch & Lehmann, 2005; X. Li, 2009). It also facilitates the establishment of new relationships and the maintenance of existing networks (Casper, 2013). Furthermore, graduates tend to secure employment close to their former university (Felsenstein, 1995). This reduces knowledge search and recruitment costs for local firms, as they can hire students from nearby universities. As a result, the cost of innovation decreases, leading to higher innovativeness of local firms (Audretsch & Lehmann, 2005).

Based on their ability to generate knowledge spillovers through personal interactions and education, it is assumed that a higher number of AI faculties in a region increases the innovativeness of firms in AI innovation ecosystems. The following hypothesis is therefore proposed:

***H1a**: AI faculties are positively related to private sector AI innovation in regional innovation ecosystems.*

When examining the dynamics of knowledge spillovers, several factors allow for the assumption that faculties influence private innovativeness with a certain time lag (Valero & Van Reenen, 2019). First, there is a time lag between the creation of knowledge within universities and its diffusion to the private sector. Tacit knowledge is initially non-verbalized, making it difficult to express and communicate (Ko & G. Liu, 2015). Therefore, faculty research may not lead to the immediate diffusion of knowledge through personal contacts. Time lags can be particularly significant in the field of AI, where knowledge tends to be highly tacit and intangible (Igna & Venturini, 2023). Similarly, immediate spillovers through student education are limited as students need time to graduate and enter industry roles before they can actively contribute to innovation (Cowan & Zinovyeva, 2013; Valero & Van Reenen, 2019).

Second, time lags can be expected in the transformation of knowledge into innovation within the private sector. Following spillovers, the acquired knowledge has to be shared internally and applied to the business context, and innovations have to be developed. Therefore, it takes time for knowledge to be transformed into marketable results (Ács et al., 2002). Additionally, the transition from innovation to intellectual property, such as patents, requires time considerations. The preparation of the application documents, the application process itself, and the time taken by the patent office for successful grants can take several years (Andersson et al., 2009; USPTO, 2024a).

Considering the temporal dynamics of knowledge spillovers and AI innovation leads to the following hypothesis:

H1b: *The positive relationship between AI faculties and private sector AI innovation in regional innovation ecosystems becomes stronger with time lags.*

3.2 Moderating Effects

Conferences can influence knowledge spillovers by creating temporal proximity between knowledge senders and receivers across organizational boundaries (Chai & Freeman, 2019). For faculties as knowledge holders, they provide a platform to interact and share tacit knowledge with stakeholders from both industry and academia (Bergman & Schubert, 2005; Henderson & Burford, 2019). Due to their limited duration, conferences require less commitment than other forms of engagement, such as collaborative research (Smeby & Trondal, 2005). Professors can disseminate knowledge through various channels, including presentations, posters, workshops, and panel discussions. Additionally, face-to-face interactions with participants enable them to comment on and challenge the shared knowledge. This provides an opportunity to further improve the quality of the research presented (Chai & Freeman, 2019).

For private companies as knowledge recipients, knowledge shared at scientific conferences can have a significant impact on innovation (Power & Malmberg, 2008), particularly in emerging technologies such as AI (Wang & K. Huang, 2021). Companies attend conferences to gain knowledge and education, as well as early access to technological developments. Attendees can build long-term relationships that provide future access to university knowledge (Cantú-Ortiz, 2014; Chai & Freeman, 2019). This reduces firms' costs associated with searching for and discovering relevant inputs (Chai & Freeman, 2019). As a result, private firms can increase their production of research (Henderson & Burford, 2019; Kyvik & Larsen, 1994) and innovation (Audretsch & Belitski, 2021).

Conferences tend to attract faculty members and industry professionals in close geographical proximity (Chai & Freeman, 2019). As such, they contribute to knowledge spillovers and the development of innovation ecosystems particularly at the regional level (Heaton et al., 2019). Therefore, the following hypothesis is posed:

H2a: *The positive relationship between AI faculties and private sector AI innovation is positively moderated by AI conferences.*

Knowledge spillovers from universities to the private sector can be further moderated by the external investment in university R&D through two main mechanisms. First, the availability of financial capital can contribute to knowledge production within the university, thereby increasing the overall base of knowledge that can be shared. External investment can offset the fixed costs associated with research and innovation processes (Ács et al., 2008). It can increase the quantity and quality of resources available for knowledge production, such as materials, advanced technologies, and personnel (Coe & Helpman, 1995). In particular, professors can obtain slack time and resources, which facilitate exploratory research (Balconi & Laboranti, 2006). In addition, financial capital can reduce the uncertainties associated with innovation (Audretsch & Lehmann, 2005), which are especially prevalent in emerging and disruptive technologies such as AI (Lazzeretti et al., 2023).

Second, external investment can enhance the dissemination of knowledge from the faculty to the private sector. New knowledge is often tacit, and the process of codification can be resource-intensive but can facilitate dissemination (Zucker et al., 2002). Moreover, financial flexibility can provide professors with free time to attend conferences, organize exchanges, maintain existing contacts, and establish new ones (Balconi & Laboranti, 2006). The size of their network can be further increased if the investment comes from the private sector. This creates a direct link with the funding company and establishes a permanent channel for knowledge spillovers (Balconi & Laboranti, 2006; X. Li, 2009). Companies may also be able to set the agenda for university research by engaging with faculty members (Balconi & Laboranti, 2006). As a result, the research conducted is closely aligned with their specific needs, increasing the likelihood that the knowledge produced will be translated into innovation.

Given the potential effects of financial resources on the creation and diffusion of knowledge by faculty, it can be assumed that external investment in university R&D strengthens the spillover of university knowledge to private firms. The following hypothesis is proposed:

H2b: *The positive relationship between AI faculties and private sector AI innovation is positively moderated by external investment in university R&D.*

The third moderator examines the role of human capital in the IT sector as a recipient of knowledge. To ensure effective knowledge spillovers from faculty members, it is important to consider actors both inside and outside the university (Schiller & Diez, 2010). This can be argued at two levels. At the industry level, the concentration of human capital implies a higher density of high-technology firms (Varga, 2000) with a potential demand for specialized knowledge in AI. By pooling their interests, these firms may have more influence on universities and the academic research agenda (Balconi & Laboranti, 2006). In addition, a higher density of IT firms indicates increased competition in the sector. This can incentivize private firms to increase their innovation efforts to differentiate and create competitive advantages.

Consequently, knowledge from academia may be transformed into tangible innovations more efficiently (Bertschek, 1995).

At the firm level, integrating external innovation inputs requires a corresponding absorptive capacity (Schiller & Diez, 2010; Qiu, X. Liu, & Gao, 2017). In the technology sector, this capacity is often reflected in the presence of IT human capital (Veugelers, 1997), which facilitates knowledge spillovers from universities through three key steps. First, a larger number of skilled employees increases the size and value of the firm's network. This allows for more interaction and knowledge sharing (Operti & Carnabuci, 2014). Second, IT specialists can build on this network by acting as spillover agents on the demand-side. They capture and filter external knowledge and share relevant insights within the organization (Zucker et al., 2002; Bergman & Schubert, 2005). Given that AI is a general-purpose technology with a dynamically evolving knowledge base, firms must constantly monitor and assimilate new knowledge. Therefore, absorptive capacity is particularly important in AI innovation (Jee & S. Sohn, 2023). Third, it is essential to effectively translate knowledge into innovation. To achieve this, findings from basic research must be adapted and integrated into business operations. Therefore, spillover agents need the ability to mobilize and exploit knowledge internally (Bergman & Schubert, 2005; Jee & S. Sohn, 2023; Varga, 2000). This process requires financial, time, and human resources. Thus, a larger IT workforce can promote AI innovation within firms (Harris & Yan, 2018; Igna & Venturini, 2023).

At both the regional and firm levels, a larger network that involves AI faculty as knowledge disseminators and IT human capital as knowledge recipients strengthens the spillover of university knowledge to the private sector. This leads to the following hypothesis:

H2c: *The positive relationship between AI faculties and private sector AI innovation is positively moderated by human capital in the IT sector.*

4 Methodology

4.1 Data and sample

The influence of faculties on AI innovation ecosystems was analyzed using several data sources. Data on US patent grants, assignees, and classification were obtained from the USPTO (2021). Details on university faculties and conferences were derived from the open source database CSRankings (2024a, 2024b), which is based on the computer science bibliography website DBLP. Conference data was further supplemented by a publication by Meho (2019). Economic, demographic and educational data on the US population were sourced from the US National Center for Science and Engineering Statistics (2024), the US Census Bureau (2024a), the US Bureau of Economic Analysis (2024), and the US Bureau of Labor Statistics (2024).

The study sample was defined based on all US counties with available AI patent information. It covers a period of 21 years, from 2000 to 2020, and includes 1,140 US counties, totaling 23,940 observations. The choice of 2000 as the starting point of the study is supported by the remarkable increase in AI research activity observed since this time. For example, 75% of scientific publications on AI were published after 2000 (WIPO, 2019). The US was chosen due to its significant role in global AI research. It has the largest amount of private investment (Stanford University, 2022b), and the second-highest numbers of publications (N. Liu et al., 2021) and patent applications worldwide (WIPO, 2019). Moreover, 13 of the world's leading 25 AI universities during the period under review are located in the US (CSRankings, 2024a).

4.2 Variables

4.2.1 Dependent variable

To measure AI innovativeness, the dependent variable *Private Patents* describes the number of AI patents granted in a county in a given year. Patents reflect the regional production of new knowledge (Ács et al., 2002; Cowan & Zinovyeva, 2013) and the results of knowledge spillovers (Bottazzi & Peri, 2003; X. Li, 2009; Yin et al, 2022), also in the context of spillovers from universities (e.g., Cowan & Zinovyeva, 2013; Van Looy et al., 2011). Patent data offers practical advantages in terms of data availability, long-term measurement, objectivity, and assignee information (Leten et al., 2014). The dependent variable is based on patent information from the USPTO, which has been used in previous innovation research (e.g., Ács et al., 2002; Toivanen & Väänänen, 2016). The study specifically uses the Artificial Intelligence Patent Dataset (AIPD) published in 2021 (USPTO, 2021). This dataset was constructed by evaluating more than six million US patent documents from 1976 to 2020 to identify the presence of AI. This was done using a combination of machine learning algorithms and manual validation by AI experts. Only patents with an identification probability above 50% were included in the present study. The authors of the dataset identified this threshold as a reliable indicator of AI patents (Giczy, Pairolero, & Toole, 2021). Moreover, it was important to differentiate the innovation activities of private firms from that of other entities. Based on previous research, a classification of assignee types available in the dataset and an additional keyword search were used to exclusively identify patents granted to private firms (Fleming, Greene, G. Li, Marx, & Yao, 2019; Igna & Venturini, 2023). The regional distribution of innovation was analyzed by examining the location of the patent assignee. Since the assignee holds the intellectual property rights to the patent, its location can be used to assign patents to a specific region (Singh, 2008; USPTO, 2024b), i.e., a US county. The complete identification process is shown in Figure 1 in the Appendix.

4.2.2 Independent variable

The independent variable *AI Faculty* refers to the number of university professors in the field of AI. Professors are known to produce high-quality research and generate knowledge spillovers through personal networks (Varga, 2000; Gofman & Jin, 2024). The number of professors in a given year is determined based on the CSRankings database, which has already been used by several scholars for previous research on AI knowledge spillovers (Gofman & Jin, 2024; Wang & K. Huang, 2021). The universities are ranked according to the number of tenured and tenure-track professors conducting research in five subfields related to AI: ‘artificial intelligence’, ‘computer vision’, ‘machine learning’, ‘natural language processing’, and ‘web and information retrieval’. The database also includes professors from fields outside computer science, such as mathematics and physics (CSRankings, 2024a; Gofman & Jin, 2024). For this study, the number of AI faculty per US university was aggregated at the county level. The analysis includes the independent variable in the actual year of faculty employment and with different time lags. This allows to account for possible sequential effects between faculty presence and actual innovation. While most research considers lags of one (C. Li et al., 2023), three (Varga et al., 2005), and five (Cowan & Zinovyeva, 2013; Valero & Van Reenen, 2019) years, this study extends the analysis to include periods of seven and nine years.

4.2.3 Moderating variables

The first moderator examined in this study is *AI Conferences*. The data is based on a list of 154 renowned computer science conferences compiled by Meho (2019). Among the five AI subtopics specified by CSRankings (see Section 4.2.2), 40 conferences were identified, 33 of which were held at least once in the US between 2000 and 2020 (Table 1). The annually changing locations of the conferences were then linked to their respective counties. This resulted in a total of 239 individual events in 75 counties. A dummy variable was used that takes the value one for counties where a conference was held within the last five years and zero otherwise.

Second, the variable *R&D Investment* is used to investigate the moderating effect of external investment in university R&D on knowledge spillovers. To achieve this, data from the Higher Education Research and Development Survey, curated by the National Center for Science and Engineering Statistics (2024), were used. The dataset represents the annual amount of external investment in university R&D at colleges and universities in the US in dollar. It has been used by several studies to examine the relationship between universities and innovation

(Varga, 2000; Woodward, Figueiredo, & Guimarães, 2006). The investments were analyzed based on the location of the universities and aggregated at the county level.

The last moderator, *IT Human Capital*, indicates the availability of human capital in the IT sector. Consistent with previous research (Igna & Venturini; 2021; Varga, 2000), this study examines total employment in the IT sector. The data were obtained from the US Bureau of Economic Analysis (2024), which provides information on total full-time and part-time employment by county, year, and industry. The industry classification follows the North American Industry Classification System, which categorizes industries based on similarities in their production processes for goods and services (US Census Bureau, 2024b).

4.2.4 Control variables

In order to avoid biased results, this study includes several control variables that may affect the innovation activity of private firms. The variables were chosen based on previous studies. First, *Total GDP* reflects the total gross domestic product (GDP) per county. A region's economic situation can be inferred from its GDP. This indicator provides access to innovation inputs such as R&D and technology (Gössling & Rutten, 2007), and facilitates the realization of the value of these factors (X. Li, 2009). Second, the *Per Capita Income* of the county population was considered. Higher income levels imply individual wealth, which can increase the demand for technological change and the propensity to invest resources in innovation (Müller, Rosenbusch, & Bausch, 2013). A third control variable used in the study was the *Unemployment Rate*, measured as the percentage of unemployed individuals in the labor force. Previous research has shown mixed effects on innovativeness (Audretsch, Dohse, & Niebuhr, 2015). Unemployment can provide opportunities for innovation by creating slack in human resources (Devece, Peris-Ortiz, & Rueda-Armengot, 2016). However, it often occurs in regions with a higher share of low-skilled workers and less developed industries, indicating less innovation in knowledge-intensive sectors (Audretsch et al., 2015; Horbach, 2013). Fourth, the study included *Population*

Density, measured as the total population per square kilometer. It implies a higher concentration of firms and business networks, as well as a more developed infrastructure, which can positively affect regional innovation (Audretsch & Fritsch, 1994; Cervero, 2001; Cowan & Zinovyeva, 2013; Gössling & Rutten, 2007). Finally, educational attainment can influence innovativeness (Valero & Van Reenen, 2019), particularly in the high-technology sector (Toivanen & Väänänen, 2016). An educated workforce enhances the ability to process technological knowledge and impacts the location decisions of innovation-producing firms (Audretsch et al., 2005; Woodward et al., 2006). Although university education appears to have a positive effect on regional innovativeness (Bottazzi & Peri, 2003), there are mixed findings for high school education (Ejermo & Hansen, 2015; Woodward et al., 2006). Thus, the regression included both *High School Education* and *University Education*, measured as the percentage of the population over 25 with the respective degree.

The variables *Total GDP, Per Capita Income, Unemployment Rate*, and *Population Density* were used by forming the natural logarithm, which fixes skewness problems and leads to better empirical results (Figures 2–9) (Ma, 2019). To reduce the impact of outliers, all control variables were winsorized at the top and bottom 1% of the distribution (Gofman & Jin, 2024). The control variables in this study were derived or calculated using datasets from the US Census Bureau, the US Bureau of Economic Analysis and the Bureau of Labor Statistics. Figure 10 in the Appendix provides an overview of the research model, including the associated hypotheses.

4.3 Estimation method

The hypotheses were tested using a regression analysis with STATA version 17.0. The sample includes observations from 2000 to 2020 with a balanced data structure, as each US county is represented across all years. A panel count data analysis was performed, which allows to control for heterogeneity across cross-sectional units, i.e., US counties, over time (Hsiao, 2007). However, panel data models run the risk of heteroskedastic error terms and autocorrelation. These two issues can lead to inconsistent and biased results (Certo & Semadeni, 2006). To detect heteroskedasticity in the residuals, a 'White test' was performed (White, 1980). Autocorrelation was tested using a 'Wooldridge test' (Wooldridge, 2001). The significant p-values indicated the presence of heteroskedasticity and autocorrelation in each model (Tables 2, 3). In this case, panel regressions can be estimated using either random effects or fixed effects models (Certo & Semadeni, 2006). The standardized regression coefficients of both models were compared using the 'xtoverid test'. This test provides results that are robust to both heteroskedasticity and within-group correlation by allowing for cluster-robust standard errors (D. Ding, 2014). The results were insignificant for all models, indicating that the random effects approach was appropriate for this study (Table 4). Therefore, generalized linear squares random effects models were used (Bertschek, 1995), clustered at the regional level (Gofman & Jin, 2024), i.e., county level. Year dummies were included to control for possible economic and technological shocks (Igna & Venturini, 2023; Runge, Schwens, & Schulz, 2021).

To test the hypotheses, the analysis sequentially added control, independent, and moderating variables. The impact of *AI Faculty* was tested using different time lags of the variable to compare the significance and coefficients of the models (Gofman & Jin, 2024; Varga et al., 2005). Additionally, the interactions between *AI Faculty* and *AI Conferences, R&D Investment,* and *IT Human Capital* were added to test the respective moderation. Several robustness tests were conducted to demonstrate that the conclusions remain valid under different assumptions.

5 Results

5.1 Summary statistics and correlations

Table 5 in the Appendix presents the summary statistics of the variables used. The first two columns show the mean and standard deviations, while the last two show the corresponding maximum and minimum values. Out of the 3,142 counties in the US, 1,140 counties were identified with at least one AI patent granted by private organizations between 2000 and 2020. On average, these counties received 20.1 patents per year. Santa Clara, California, was granted the highest number of AI patents in 2020 with 8,196 patents. Across all counties considered, the average number of faculties per year was 0.56, with Middlesex, Massachusetts, having the highest number of professorships at 88 in 2020.

The correlation matrix (Table 6) indicates significant intercorrelations between several variables. Therefore, variance inflation factors (VIFs) were observed to test for potential multicollinearity problems (Table 7). A VIF greater than ten indicates multicollinearity problems and is considered problematic for standard error calculations (Snee, 1973). The main regression yielded a maximum VIF of 3.85 and a mean VIF of 2.05. For all models in this study, the VIFs were also less than ten, indicating that multicollinearity did not significantly affect the results.

5.2 Hypotheses tests

Table 8 presents the results of the regression analysis. Model 1 shows the effect of the control variables only. Model 2 examines the main regression of *AI Faculty* on *Private Innovation*. Models 3 to 6 test the main regression with time lags for *AI Faculty* of three, five, seven, and nine years. The moderation effects are examined in the Models 7 to 9.

Model 1 shows significant estimates for *Per Capita Income, Population Density*, and *High School Education*. *Per Capita Income* and *Population Density* are positively associated with a region's innovation activity, while a higher percentage of individuals with a high school degree appears to have a negative effect. This relationship may be explained by the variability in the quality of high school education. This aspect is not captured by the variable, making it a less reliable predictor of innovation (Ejermo & Hansen, 2015). Furthermore, high schools only provide a very general knowledge base, while AI innovation requires specific technological knowledge. However, this finding presents opportunities for further investigation.

Hypothesis 1a, which suggests that *AI Faculty* has a positive impact on innovation activity, is supported by the results of Model 2 ($\beta = 17.82$; $p = .01$). This indicates that regions with a higher presence of AI faculties have a higher number of AI patents owned by private firms. Additionally, Hypothesis 1b is confirmed by the regression results of Models 3 to 6. Compared to Model 2, the coefficient for the impact of university faculties on innovative activity appears to increase after three ($\beta = 23.37$; $p = .02$) and five years ($\beta = 23.86$; $p = .01$). The highest coefficient is observed after seven years ($\beta = 25.33$; $p = .02$), followed by a decline after nine years ($\beta = 13.41$; $p = .02$). These findings indicate that the impact of the university faculty on private innovation increases with a certain time lag, reaching its peak after approximately seven years.

Models 7, 8, and 9 show the regression results after including moderating variables. The results do not support Hypothesis 2a, which predicted a positive interaction term between *AI Faculty* and *AI Conferences*, as the regression coefficient of the interaction term in Model 7 is insignificant ($\beta = -3.98$; $p = .46$). Similarly, Hypothesis 2b is not supported by Model 8 ($\beta = .00$; $p = .80$), which proposed that *R&D Investment* strengthens the relationship between faculties and innovation activity. Finally, referring to Hypothesis 2c, the results indicate a significant coefficient for the interaction term between *AI Faculty* and *IT Human Capital* in Model 8 ($\beta = .01$; $p = .03$). As the coefficient is close to zero, the moderating effect of this variable was further interpreted using a marginal effects approach (Busenbark, Graffin, Campbell, & Lee, 2022). Figure 11 illustrates the moderation effect of IT employment on the relationship between faculties and innovation activity. Different levels of the *IT Human Capital* variable were defined based on its distribution, ranging from the 1st to the 99th percentile. The study indicates that the moderating effect becomes statistically significant at the 95th ($\beta = 6.87$; $p = .01$) and 99th percentiles ($\beta = 31.77$; $p = .02$) of the variable (Table 9). It can be inferred that employment in the IT sector strengthens the impact of knowledge spillovers from AI faculty on patenting activity of private firms when it increases to high levels.

5.3 Robustness checks

As stated in Section 4.3, several robustness checks were performed to confirm the results (Table 10). Following Igna and Venturini (2023), alternative estimation methods were used for the main regression, namely a fixed effects (Model R1), a negative binomial (Model R2), and a GEE regression analysis (Model R3). All models yielded the same results, confirming that AI faculties have a positive impact on the AI patenting activity of private firms. To provide a more comprehensive regional analysis, another regression was conducted using state-level clustering instead of county-level clustering. The results indicate significant estimates for the impact of faculty on innovativeness (Model R4). This is consistent with the findings of Ács et al. (2002) and Audretsch and Feldman (1996) regarding knowledge spillovers from universities to the private sector at the state level. Furthermore, to test the robustness of the main independent variable, *AI Faculty* was treated as a dummy variable instead of a count variable (Kinzius, Sandkamp, & Yalcin, 2019). Again, the results remained stable with this modification (Model R5).

Further robustness checks were conducted by examining sampling issues. First, the total period was divided into two parts: from 2000 to 2010 and from 2011 to 2020. This allowed for the study of the exponential developments of the AI economy in the later period (Igna & Venturini, 2023). Second, a regression model was estimated using a subsample that only included counties with at least one faculty member during the observed period (Valero & Van Reenen, 2019). The estimates indicate that all results are robust to these specifications, confirming the previous findings (Models R6–R8). All robustness checks were carried out not only for the main regression, but were extended to all other models, including time lags and moderation effects. The results remained consistent with those presented in Table 10.

6 Discussion

6.1 Contributions to theory

This study tested the hypothesis that AI faculties at universities positively influence private innovation in regions through knowledge spillovers. Patenting in AI innovation ecosystems was analyzed at the county level in the US for the period 2000 to 2020. The results showed that AI faculties have a significant positive impact on patenting through private innovation. This effect increases over a period of up to seven years when time lags are taken into account. Additionally, the study analyzed potential moderators that could enhance the spillover effect from AI faculty to the private sector. Although the presence of AI conferences in the region and the level of external investment in university R&D were hypothesized to positively moderate the spillover effect, neither variable showed a significant influence. However, the level of human capital in the IT sector supported the faculty spillover effect at higher levels of the moderator variable. From a theoretical perspective, this study extends several strands of the literature and provides suggestions for further research.

The present study contributes to previous research on innovation ecosystems and knowledge spillovers. In particular, it aligns with the literature that examines the development of ecosystems from a bottom-up perspective (e.g., Sultana et al., 2023; Van Looy et al., 2011). It confirms the importance of universities in promoting innovation in both sectors and regions (e.g., Cowan & Zinovyeva, 2013; Davies et al., 2020; Heaton et al., 2019; G. Xu et al., 2018), and highlights their role as developers of innovation ecosystems (Heaton et al., 2019; Van Looy et al., 2011). The present results expand on these findings by examining not only the relevant actors within ecosystems, but also within universities, and explain the mechanisms through which these actors influence innovation. Thereby, they support the literature that identifies a positive relationship between universities and innovation through knowledge spillovers (e.g., Audretsch, 2012; Simmie, 2002; Varga, 2000), particularly through the support of spillover agents (e.g., Zucker et al., 2002). Other studies have primarily focused on the role of graduates or general academic staff (e.g., Andersson et al., 2009; Audretsch & Lehmann, 2005). The present study highlights faculties as crucial facilitators of spillovers from universities to the private sector. Previous research has not fully examined the channels through which these faculty spillovers occur. They have been primarily studied in terms of education, demonstrating that professors influence the private sector through their graduates who establish startups (e.g., Gofman & Jin, 2024; Power & Malmberg, 2008). However, by analyzing patents from all private firms rather than the number of startups, the present study suggests that spillover channels from professors to the private sector go beyond education and include interactions with all types of industry representatives. It is recommended that future research examines the impact of professors in a more nuanced manner, taking into account different firm characteristics such as age, size, or ownership structure. Further conclusions on spillover channels can be drawn by combining the results of this study with those of Igna and Venturini (2023), who find no significant effects of university patenting on private innovation. This indicates that passive innovation activities by universities may not be sufficient to generate spillovers. Rather, active engagement by faculties as spillover agents are required to actually influence knowledge diffusion and the development of innovation ecosystems (Audretsch, 2012).

Furthermore, this study makes contributions to the AI literature, particularly in the areas of AI innovation ecosystems and AI education. Prior literature on innovation ecosystems has paid limited attention to AI. Therefore, conclusions had to be drawn from studies on high-technology innovation ecosystems (e.g., Varga, 2000; G. Xu et al., 2018). Nevertheless, AI has specific research requirements due to its future relevance (Gofman & Jin, 2024) and unique technological characteristics (Igna & Venturini, 2023). Previous research has primarily focused on the impact of AI technologies on the overall innovation activities of firms and regions (e.g., Bessen et al., 2022; Lazzeretti et al., 2023; C. Li et al., 2023; K. Yin et al., 2022). By using the

AIPD, which only reflects AI patents, this study allows for a specific focus on AI innovation ecosystems. It also contributes to the literature on AI education, which has examined the use of AI technologies in lectures (e.g., Shum & Luckin, 2019; Zawacki-Richter et al., 2019) and curriculum design of AI courses (e.g., Langley, 2019; Nguyen et al., 2020). As previously mentioned, the impact of AI faculties has only been measured in terms of startup creation (Gofman & Jin, 2024). This study provides a more comprehensive understanding of how AI education influences the development of AI innovation ecosystems as a whole.

Moreover, this study supports prior research that emphasizes the significance of geographical proximity in knowledge spillovers and innovation ecosystems (e.g., Audretsch & Lehmann, 2005; Autio et al., 2018; Etzkowitz & Leyesdorff, 2000; X. Li, 2009). However, in the context of AI, regional spillovers have only been examined at the level of metropolitan statistical areas (e.g., Wang & K. Huang, 2021). In response to Audretsch and Feldman's (1996) call to consider spillovers at smaller regional scales, this study also found significant effects of AI spillovers within counties. In general, these results are consistent with the theory that geographic proximity reduces transaction costs (Autio et al., 2018) and increases opportunities for faculty to share knowledge (Zucker et al., 2002). Upon closer examination, the present study reveals significant regional effects in terms of people-related factors, specifically AI faculty and IT human capital, while more objective factors such as conferences and external investment remain insignificant. This supports the idea that proximity is particularly important for the exchange of tacit knowledge by enabling personal interactions (X. Li, 2009; Simmie, 2002; Varga, 2000).

This study enhances the understanding of knowledge spillovers by introducing a temporal dimension. It confirms the hypothesis that the accumulation and transformation of knowledge spillovers into innovation require a certain amount of time. These findings contradict the results of Varga et al. (2005), who found no significant differences between immediate and delayed effects. Previous literature, which has only focused on effects between one and five years

(Cowan & Zinovyeva, 2013; Igna & Venturini, 2023, C. Li et al., 2023; Valero & Van Reenen, 2019), is extended by systematically comparing regression models with different degrees of time lags. While the effect of faculties on private sector patenting is positive and significant in all models, the strongest effect occurs after approximately seven years. This can be explained by the specific characteristics of the underlying research focus. AI is an emerging technology that relies on highly tacit and complex knowledge (J. Xu & Babaian, 2021). Therefore, the search for appropriate knowledge and the innovation process may take longer than in other research areas. Furthermore, using patent grants as a measure of innovation can cause additional delays since the application and granting procedure can take several years (Andersson et al., 2009; Varga et al., 2005). Alternative measures of innovative activity, such as market introductions of new products (Fritsch, 2002), may result in faster manifestation of spillovers in measurable innovation outcomes. However, the present results should be treated with caution as the number of observations included in the models decreases due to the shorter time periods considered for the independent variable (Table 8; Models 2–6).

Several moderators were examined to provide deeper insights into knowledge spillovers from universities. The addition of AI conferences as a moderator did not significantly affect the impact of AI faculty on private innovation. This contradicts previous findings that conferences are important channels for knowledge spillovers (e.g., Audretsch & Belitski, 2021), especially in the field of AI (e.g., Cantú-Ortiz, 2014). There are several possible explanations for the non-significant results. First, Chai and Freeman (2019) found that professors may benefit less from conferences than junior researchers. This is due to their already large networks, which may lower their incentives to actively engage and make new contacts. Second, several studies have shown that knowledge spillovers at conferences do not occur automatically. Rather, they depend on the media and technologies used to present knowledge (De Simone et al., 2001; Rowe & Ilic, 2009). This is particularly relevant for new, tacit AI knowledge. In addition, Zucker et al.

(2002) note that knowledge spillovers through personal contacts always require scientists to be willing to share knowledge. Thus, the value generated by the spillover must exceed the cost of sharing, which is comparatively high for tacit knowledge. In addition, conferences often involve admission fees and physical attendance over several days, which may decrease the incentive for professors to participate and share knowledge. Third, the impact of conferences may not be localized at the regional level. Research indicates that benefits of conferences are greater for international researchers (Kyvik & Larsen, 1994), and occur within specific subfields of AI rather than in geographical regions (Cantú-Ortiz, 2014). While conferences can create temporal proximity between participants from different locations (Chai & Freeman, 2019), the effects may become unmeasurable at the county level when researchers return to their home region. The present study adds to previous literature by emphasizing that knowledge spillovers from conferences should not automatically be assumed. To ensure their effectiveness for regional innovation, a more nuanced perspective on the characteristics of conferences and their participants is required. Moreover, extending the sample of events analyzed to include other academic disciplines, such as various areas of computer science and engineering, could provide additional insights.

Furthermore, this study did not find a significant moderating effect of external investment in university R&D. This contradicts the assumption that investment in university research increases spillovers through mechanisms such as an expanded knowledge base, slack resources of professors, and increased interactions through funding relationships (e.g., Balconi & Laboranti, 2006; Coe & Helpman, 1995; X. Li, 2009). The results indicate that investment in university research alone may not be sufficient to generate knowledge spillovers and promote regional innovation. This can be explained by three possible approaches. First, Meléndez et al. (2020) highlight the importance of intermediaries in leveraging knowledge produced at universities. To reduce the gap between academia and the market, financial resources should be directed towards institutions that support spillover mechanisms, such as technology transfer offices, or towards individuals who take on the role of knowledge spillover agents. Second, Audretsch (2012) argues that increased knowledge production at universities may not necessarily align with the needs of industry. To be translated into private innovation, knowledge must be designed for practical application rather than for internal university use. Particularly in the emerging field of AI, which still has significant research gaps (J. Xu & Babaian, 2021), this can result in a disparity between academic supply and market demand. Similarly, Akcigit et al. (2020) found a non-linear relationship between research investment and innovation output. This poses a risk of over-subsidizing either basic or applied research, making investment less efficient for innovation. Due to data limitations, the present study does not differentiate between the types of research targeted by the investments. Therefore, future research is encouraged to adopt a more nuanced approach to the internal allocation of resources when investigating the impact of investment on knowledge spillovers from universities.

Finally, the moderating effect of IT human capital on knowledge spillovers is significant, which is consistent with previous research. It confirms the importance of both supply- and demand-side spillover agents (Meléndez et al., 2020; Schiller & Diez, 2010; Zucker et al., 2002). At the industry level, scholars have demonstrated that ecosystem size has a positive impact on spillovers (Operti & Carnabuci, 2014). At the firm level, absorptive capacity has been highlighted as important for enabling knowledge integration and transformation (e.g., Audretsch, 2012; Audretsch & Lehmann, 2005; Harris & Yan, 2018; Nie et al., 2022). The present study contributes to previous literature by allowing for a deeper analysis of the variable through the adopted marginal effects approach. The analysis indicates that the moderating effect is statistically significant only when the variable exceeds a certain threshold. These results suggest that human capital supports faculty-driven knowledge spillovers and AI innovation primarily in counties with a comparatively high number of IT professionals. There are several potential explanations for this finding. First, a comparatively high level of IT employment may indicate a greater presence of large firms in the region, which are more likely to have slack resources (Sharfman, Wolf, Chase, & Tansik, 1988). Due to the young and disruptive nature of AI (J. Xu & Babaian, 2021), more effort is needed to effectively transform knowledge into tangible innovations. Slack resources can facilitate the exploration of distant, new knowledge, thereby promoting knowledge spillovers in areas new to the firm (Troilo, De Luca, & Atuahene-Gima, 2013). Moreover, slack resources can positively impact radical innovation (Medase, 2020) by increasing creativity (Bourgeois, 1981), reducing uncertainty associated with innovation, and facilitating the exploitation of tacit knowledge (Dolmans, Van Burg, Reymen, & Romme, 2014; Lecuona & Reitzig, 2013). A second explanation can be derived from the findings of Schiller and Diez (2010), who propose the need for a "critical mass" (p. 281) of spillover agents on the demand side. The authors argue that exceeding a certain threshold of experts can increase the visibility and funding opportunities of the receiving institutions, making spillovers more attractive. However, they only focus on spillovers between academic institutions. The present study extends their findings by demonstrating that surpassing a threshold number of spillover agents is also crucial for interactions with industry.

6.2 Practical implications

The results of this study have several practical implications for policymakers, universities, and companies. Governments have already taken various measures to promote innovation in AI due to its increasing importance (C. Zhang & Lu, 2021). The present study highlights a concrete lever for policymakers: While it is difficult to directly influence spillovers within the private sector, they can enhance spillovers from universities to industry (Audretsch & Lehmann, 2005). This requires a reassessment of the role of universities, recognizing them not solely as producers of knowledge, but also as key drivers of innovation (Davies et al., 2020; Van Looy et al, 2011). Governments can facilitate access to collaborative research and exchange (Zucker et al., 2002) by establishing publicly funded research consortia or platforms that connect different actors within the ecosystem. Such targeted AI networks can encourage the establishment of relationships between academia and industry, thereby increasing spillovers in the long run. In addition, they enable the alignment of research with industry needs, which increases the likelihood of innovation (Balconi & Laboranti, 2006). However, the rejection of Hypothesis 2a indicates that not all channels of exchange automatically affect faculty spillovers and innovation. Therefore, the careful selection of mechanisms that promote spillovers may require further investigation.

A second lever to consider is the strategic investment of governments and universities. The rejection of Hypothesis 2b and the findings of Akcigit et al. (2020) on over-subsidization suggest that increased resource provision alone may not be sufficient. Therefore, government investment in universities and the internal allocation of resources should be done carefully (Wang & K. Huang, 2021). The present results emphasize the importance of AI faculty and recommend increasing the number of AI professors in US universities, particularly due to the growing demand for AI education (J. Xu & Babaian, 2021). Furthermore, it is crucial that research investments in universities are not only directed towards knowledge production, but also towards spillover mechanisms. These mechanisms may involve the establishment of technology transfer offices or university-led venture capital organizations (Meléndez et al., 2020).

Finally, implications can be drawn for companies within the AI innovation ecosystem. Innovative firms need to recognize universities as a valuable source of knowledge, especially in emerging sectors such as AI. Managers should seek to proactively influence the academic research agenda when specific needs arise (Balconi & Laboranti, 2006) to better align research outcomes with industry needs and strengthen the relationship between business and academia. However, to achieve this, companies must adopt a culture of openness to external inputs and innovation orientation (West & Bogers, 2013). This can be supported by external change agents (Mol & Birkinshaw, 2014). Managers should recognize the value of their employees as knowledge spillover agents and encourage them to interact with universities (Zucker et al., 2002). For instance, firms could offer academic scouting or support in university incubators (Power & Malmberg, 2008). Additionally, the present study demonstrated that managers can improve the innovative activity of their firm by increasing its absorptive capacity (West & Bogers, 2013) and creating slack resources (Medase, 2020). To identify and convert knowledge into innovation more effectively, firms can expand the skills of existing employees and hire new professionals, particularly in high-technology fields (Mason, Rincón-Aznar, & Venturini, 2019). Lastly, firms can facilitate innovative activity though strategic location decisions. This study shows that knowledge externalities are regionally bound, particularly in emerging and tacit knowledge domains. To benefit from the knowledge created, firms innovating in AI should consider locating near universities with AI faculties (Wang & K. Huang, 2021). This is supported by empirical evidence that the research intensity of universities in a region positively influences firms' location decisions (e.g., Audretsch et al., 2005; Belderbos, Van Roy, Leten, & Thijs, 2014; Siedschlag, Smith, Turcu & X. Zhang, 2013; Woodwart et al., 2006).

6.3 Limitations and future research

There are several limitations to this study that could potentially affect the results. First, the internal validity of the study may be limited by the choice of variables. The total number of patents is used as a measure of AI innovation, which reflects the quantity rather than the quality of patents (X. Li, 2009) and ignores the actual value creation for the region (Power & Malmberg, 2008). In the context of AI technologies, more and more companies are releasing their innovations as open source software. Instead of protecting the software as intellectual property, it is made available on online platforms and in developer networks (WIPO, 2019). As a result, patent data from the AIPD may not accurately reflect the level of AI innovation. To enhance the robustness of the hypotheses, future research could consider alternative measures of innovation, such as the number of citations to determine the quality of a patent (Cowan & Zinovyeva, 2013), the number of products launched (Fritsch, 2002; X. Li, 2009), or the total number of detectable AI software, codes, and patents. Furthermore, it is important to consider potential omitted control and moderator variables. Additional factors, such as university spin-offs and R&D collaborations, may influence the academic-private sector relationship and lead to increased spillovers (X. Li, 2009; Wennberg, Wiklund, & Wright, 2011; Zucker et al., 2002). Also, this study only provides insights into two parts of the triple helix model (Etzkowitz & Leyesdorff, 2000), excluding the influence of governments. Incorporating a top-down perspective, such as examining the effects of different regulations and subsidies on the intensity of spillovers, could provide valuable insights.

Second, the study's external validity may be limited by the geographical scope and definition of regional boundaries. Focusing solely on the US, with its high level of knowledge production and AI innovation, raises questions about the generalizability of the findings. Other countries may have lower average levels of research and innovation, or different regulatory regimes and regional structures. To achieve a universally applicable understanding of the impact of faculties on regional innovation ecosystems, future research should broaden its geographical scope and conduct studies in various countries and regions. Moreover, the study only examines spillovers within US counties, overlooking potential spillovers to neighboring regions where faculty and other variables could influence the innovativeness of the private sector. Effects may occur in the region of the university but extend beyond county boundaries, for example through faculty networking or graduate mobility. Future research could investigate the impact of faculties on neighboring counties (Leten et al., 2014) or use the absolute distance to universities as a basis for analysis (Woodwart et al., 2006).

A final limitation of the results is the potential bias caused by dynamic endogeneity (J. Li, H. Ding, Hu & Wan, 2021). Innovation is not a linear process where academic research is disseminated to private firms and translated into innovation. Instead, research activity can be shaped and increased by the demand side in a dynamic and interactive process (Power & Malmberg, 2008). This is supported by the findings of E. Sohn (2021), which suggest that regional innovation by firms has an impact on academic research output. Consequently, the level of patenting by private firms may affect the number of AI faculties. This could be due to the increased attractiveness of regions for AI professors, who actively choose areas with a strong industrial presence and the potential for valuable relationships. Furthermore, universities may become more aware of the importance of AI and increase their investment in AI education and faculties. To mitigate these endogeneity biases, time lags were introduced, which showed increasing effects after several years. However, further refinement could include different estimators or additional instrumental variables (J. Li et al., 2021). Although these considerations were beyond the scope of the present study, they provide valuable input for future research.

7 Conclusion

This study discusses a potential relationship between AI faculty and private sector innovation in AI innovation ecosystems. Based on the literature on innovation ecosystems and knowledge spillovers, it is hypothesized that AI professors have a positive impact on private firm innovation within a region. This influence arises from knowledge spillovers, facilitated by personal interactions within the professors' broad networks in academia and industry, as well as through the education of students and industry professionals. A random effects regression analysis was conducted using panel data from the USPTO over the period 2000 to 2020. The study finds a significant positive relationship between the number of AI faculties and the number of AI patents granted to private firms within the same US county.

These results contribute to the existing literature on knowledge spillovers and the relevant actors within innovation ecosystems. They highlight the impact of universities, particularly their faculties, in driving innovation. The channels of knowledge spillovers from faculty are further examined by considering various moderating factors. The results show that human capital in the IT sector has a positive effect on knowledge spillovers at higher levels of the variable. However, there is no significant impact of AI conferences and external investment in university R&D. This shows that the mere existence of exchange platforms and resources may not be sufficient, and highlights the importance of actively mobilizing tacit knowledge through spillover agents. Moreover, the present study advances the understanding of spillover dynamics by demonstrating that the impact of faculty on innovation intensifies over time, with the strongest effects observed after approximately seven years. This clarifies the complexity of the processes involved in AI innovation and patenting. By focusing exclusively on AI faculty and patents, this study is the first to identify the role of spillovers from academic individuals to the private sector in this field. Thereby, it also complements the literature on AI innovation ecosystems and AI education. In addition, several practical implications were derived. It is recommended that universities and governments leverage the role of faculty and promote exchanges within innovation ecosystems. Companies should actively engage with academia, increase their absorptive capacity, and consider nearby universities in their location decisions. Finally, this study discusses potential limitations related to the selection and explanatory power of the variables, the external validity of the results due to its geographical scope, and endogeneity issues. Therefore, it leaves room for further research and refinement.

Bibliography

Ács, Z. J., Braunerhjelm, P., Audretsch, D. B., & Carlsson, B. (2008). The knowledge spillover theory of entrepreneurship. *Small Business Economics*, *32*(1), 15-30. https://doi.org/10.1007/s11187-008-9157-3

Ács, Z. J., Anselin, L., & Varga, A. (2002). Patents and innovation counts as measures of regional production of new knowledge. *Research Policy*, *31*(7), 1069-1085. https://doi.org/10.1016/s0048-7333(01)00184-6

Agarwal, R., Audretsch, D. B., & Sarkar, M. (2010). Knowledge spillovers and strategic entrepreneurship. *Strategic Entrepreneurship Journal*, *4*(4), 271-283. https://doi.org/10.1002/sej.96

Agrawal, A. (2001). University-to-industry knowledge transfer: literature review and unanswered questions. *International Journal Of Management Reviews*, *3*(4), 285-302. https://doi.org/10.1111/1468-2370.00069

Akcigit, U., Hanley, D., & Serrano-Velarde, N. (2020). Back to Basics: Basic Research Spillovers, Innovation Policy, and Growth. *The Review Of Economic Studies*, *88*(1), 1-43. https://doi.org/10.1093/restud/rdaa061

Alexy, O., George, G., & Salter, A. (2013). Cui Bono? The Selective Revealing of Knowledge and Its Implications for Innovative Activity. *Academy Of Management Review*, *38*(2), 270-291. https://doi.org/10.5465/amr.2011.0193

Andersson, R., Quigley, J. M., & Wilhelmsson, M. (2009). Urbanization, productivity, and innovation: Evidence from investment in higher education. *Journal Of Urban Economics*, *66*(1), 2-15. https://doi.org/10.1016/j.jue.2009.02.004

Audretsch, D. B. (2012). From the entrepreneurial university to the university for the entrepreneurial society. *The Journal Of Technology Transfer*, *39*(3), 313-321. https://doi.org/10.1007/s10961-012-9288-1

Audretsch, D. B., & Belitski, M. (2021). Frank Knight, uncertainty and knowledge spillover entrepreneurship. *Journal Of Institutional Economics*, *17*(6), 1005-1031. https://doi.org/10.1017/s1744137421000527

Audretsch, D. B., Dohse, D., & Niebuhr, A. (2015). Regional unemployment structure and new firm formation. *Papers in Regional Science*, *94*, 115-138. https://doi.org/10.1111/pirs.12169

Audretsch, D. B., & Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. *The American economic review, 86*(3), 630-640. https://www.jstor.org/stable/2118216

Audretsch, D. B., & Fritsch, M. (1994). The Geography of Firm Births in Germany. *Regional Studies*, *28*(4), 359-365. https://doi.org/10.1080/00343409412331348326

Audretsch, D. B., & Keilbach, M. (2008). Resolving the knowledge paradox: Knowledge-spillover entrepreneurship and economic growth. *Research Policy*, *37*(10), 1697-1705. https://doi.org/10.1016/j.respol.2008.08.008

Audretsch, D. B., & Lehmann, E. E. (2005). Does the Knowledge Spillover Theory of Entrepreneurship hold for regions? *Research Policy*, *34*(8), 1191-1202. https://doi.org/10.1016/j.respol.2005.03.012

Audretsch, D. B., Lehmann, E. E., & Warning, S. (2005). University spillovers and new firm location. *Research Policy*, *34*(7), 1113-1122. https://doi.org/10.1016/j.respol.2005.05.009

Autio, E., Nambisan, S., Thomas, L. D., & Wright, M. (2018). Digital affordances, spatial affordances, and the genesis of entrepreneurial ecosystems. *Strategic Entrepreneurship Journal, 12*(1), 72-95. https://doi.org/10.1002/sej.1266

Balconi, M., & Laboranti, A. (2006). University-industry interactions in applied research: The case of microelectronics. *Research Policy*, *35*(10), 1616-1630. https://doi.org/10.1016/j.respol.2006.09.018

Bednář, P., Danko, L., & Smékalová, L. (2021). Coworking spaces and creative communities: making resilient coworking spaces through knowledge sharing and collective learning. *European Planning Studies*, *31*(3), 490-507. https://doi.org/10.1080/09654313.2021.1944065

Belderbos, R., Roy, V., Leten, B., & Thijs, B. (2014). Academic Research Strengths and Multinational Firms' Foreign R&D Location Decisions: Evidence from R&D Investments in European Regions. *Environment And Planning A: Economy And Space*, *46*(4), 920-942. https://doi.org/10.1068/a45536

Belenzon, S., & Schankerman, M. (2013). Spreading the Word: Geography, Policy, and Knowledge Spillovers. *The Review Of Economics And Statistics*, *95*(3), 884-903. https://doi.org/10.1162/rest_a_00334

Beltagui, A., Rosli, A., & Candi, M. (2020). Exaptation in a digital innovation ecosystem: The disruptive impacts of 3D printing. *Research Policy*, *49*(1), 103833. https://doi.org/10.1016/j.respol.2019.103833

Bergman, E. M., & Schubert, U. (2005). Spillovers and innovation, environment and space: policy uncertainties and research opportunities. In *Spillovers and Innovations*, 157-177. Vienna: Springer.

Berman, E. M. (1990). The economic impact of industry-funded university R&D. *Research Policy*, *19*(4), 349-355. https://doi.org/10.1016/0048-7333(90)90018-2

Bertschek, I. (1995). Product and Process Innovation as a Response to Increasing Imports and Foreign Direct Investment. *The Journal Of Industrial Economics*, *43*(4), 341-375. https://doi.org/10.2307/2950548

Bessen, J., Impink, S. M., Reichensperger, L., & Seamans, R. (2022). The role of data for AI startup growth. *Research Policy*, *51*(5), 104513. https://doi.org/10.1016/j.respol.2022.104513

Bloom, N., Schankerman, M., & Van Reenen, J. (2013). Identifying Technology Spillovers and Product Market Rivalry. *Econometrica*, *81*(4), 1347-1393. https://doi.org/10.3982/ecta9466

Bottazzi, L., & Peri, G. (2003). Innovation and spillovers in regions: Evidence from European patent data. *European Economic Review*, *47*(4), 687-710. https://doi.org/10.1016/s0014-2921(02)00307-0

Bourgeois, L. J. (1981). On the Measurement of Organizational Slack. *Academy Of Management Review*, *6*(1), 29-39. https://doi.org/10.5465/amr.1981.4287985

Bozeman, B., & Gaughan, M. (2007). Impacts of grants and contracts on academic researchers' interactions with industry. *Research Policy*, *36*(5), 694-707. https://doi.org/10.1016/j.respol.2007.01.007

Busenbark, J. R., Graffin, S. D., Campbell, R. J., & Lee, E. Y. (2022). *A marginal effects approach to interpreting main effects and moderation. Organizational Research Methods, 25*(1), 147-169. https://doi.org/10.1177/1094428120976838

Buzard, K., Carlino, G. A., Hunt, R. M., Carr, J. K., & Smith, T. (2020). Localized knowledge spillovers: Evidence from the spatial clustering of R&D labs and patent citations. *Regional Science And Urban Economics*, *81*, 103490. https://doi.org/10.1016/j.regsciurbeco.2019.103490

Callon, M. (1994). Is Science a Public Good? Fifth Mullins Lecture, Virginia Polytechnic Institute, 23 March 1993. *Science, Technology, & Human Values*, *19*(4), 395-424. https://doi.org/10.1177/016224399401900401

Cantú-Ortiz, F. J. (2014). Advancing artificial intelligence research and dissemination through conference series: Benchmark, scientific impact and the MICAI experience. *Expert Systems With Applications*, *41*(3), 781-785. https://doi.org/10.1016/j.eswa.2013.08.008

Casper, S. (2013). The spill-over theory reversed: The impact of regional economies on the commercialization of university science. *Research Policy*, *42*(8), 1313-1324. https://doi.org/10.1016/j.respol.2013.04.005

Certo, S. T., & Semadeni, M. (2006). Strategy Research and Panel Data: Evidence and Implications. *Journal Of Management*, *32*(3), 449-471. https://doi.org/10.1177/0149206305283320

Cervero, R. (2001). Efficient urbanisation: economic performance and the shape of the metropolis. *Urban Studies, 38*(10), 1651-1671. https://doi.org/10.1080/00420980120084804

Chai, S., & Freeman, R. B. (2019). Temporary colocation and collaborative discovery: Who confers at conferences. *Strategic Management Journal*, *40*(13), 2138-2164. https://doi.org/10.1002/smj.3062

Coe, D. T., & Helpman, E. (1995). International R&D spillovers. *European Economic Review*, *39*(5), 859-887. https://doi.org/10.1016/0014-2921(94)00100-e

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, *35*(1), 128-152. https://doi.org/10.2307/2393553

Cohendet, P., & Meyer-Krahmer, F. (2001). The theoretical and policy implications of knowledge codification. *Research Policy*, *30*(9), 1563-1591. https://doi.org/10.1016/s0048-7333(01)00168-8

Cooke, P., Uranga, M. G., & Etxebarria, G. (1997). Regional innovation systems: Institutional and organisational dimensions. *Research policy, 26*(4-5), 475-491. https://doi.org/10.1016/S0048-7333(97)00025-5

Cowan, R., & Zinovyeva, N. (2013). University effects on regional innovation. *Research Policy*, *42*(3), 788-800. https://doi.org/10.1016/j.respol.2012.10.001

CSRankings (2024a). *Computer Science Rankings*. Accessed on 18. February 2024 from https://csrankings.org/#/index?all&us

CSRankings (2024b). *FAQ Computer Science Rankings*. Accessed on 18. February 2024 from https://csrankings.org/faq.html

Davies, G., Flanagan, J., Bolton, D., Roderick, S., & Joyce, N. (2020). University knowledge spillover from an open innovation technology transfer context. *Knowledge Management Research, & Practice*, *19*(1), 84-93. https://doi.org/10.1080/14778238.2020.1746204

De Simone, R., Rodrian, J., Osswald, B., Sack, F., De Simone, E., & Hagl, S. (2001). Initial experience with a new communication tool: the 'Digital Interactive Poster Presentation'. *European Journal Of Cardio-Thoracic Surgery*, *19*(6), 953-955. https://doi.org/10.1016/s1010-7940(01)00694-7

Devece, C., Peris-Ortiz, M., & Rueda-Armengot, C. (2016). Entrepreneurship during economic crisis: Success factors and paths to failure. *Journal Of Business Research*, *69*(11), 5366-5370. https://doi.org/10.1016/j.jbusres.2016.04.139

Ding, D. X. (2014). The effect of experience, ownership and focus on productive efficiency: A longitudinal study of US hospitals. *Journal of Operations Management, 32*(1-2), 1-14. https://doi.org/10.1016/j.jom.2013.10.002

Dolmans, S., Van Burg, E., Reymen, I., & Romme, A. (2014). Dynamics of Resource Slack and Constraints: Resource Positions in Action. *Organization Studies*, *35*(4), 511-549. https://doi.org/10.1177/0170840613517598

Doloreux, D., & Turkina, E. (2021). New path creation in the artificial intelligence industry: regional preconditions, new actors and their collective actions, and policies. *Regional Studies*, *55*(10-11), 1751-1763. https://doi.org/10.1080/00343404.2021.1919610

Döring, T., & Schnellenbach, J. (2006). What do we know about geographical knowledge spillovers and regional growth?: A survey of the literature. *Regional Studies*, *40*(3), 375-395. https://doi.org/10.1080/00343400600632739

Ejermo, O., & Hansen, H. K. (2015). How important are local inventive milieus: The role of birthplace, high school and university education. *Geoforum*, *65*, 387-397. https://doi.org/10.1016/j.geoforum.2014.12.002

Etzkowitz, H., & Leydesdorff, L. (2000). The dynamics of innovation: from National Systems and “Mode 2” to a Triple Helix of university-industry-government relations. *Research Policy*, *29*(2), 109-123. https://doi.org/10.1016/s0048-7333(99)00055-4

Felsenstein, D. (1995). Dealing with “induced migration” in university impact studies. *Research in Higher Education*, *36*(4), 457-472. https://doi.org/10.1007/bf02207906

Fleming, L., Greene, H., Li, G., Marx, M., & Yao, D. A. (2019). Government-funded research increasingly fuels innovation. *Science*, *364*(6446), 1139-1141. https://doi.org/10.1126/science.aaw2373

Fritsch, M. (2002). Measuring the Quality of Regional Innovation Systems: A Knowledge Production Function Approach. *International Regional Science Review*, *25*(1), 86-101. https://doi.org/10.1177/016001702762039394

Gál, Z., & Ptáček, P. (2011). The Role of Mid-Range Universities in Knowledge Transfer in Non-Metropolitan Regions in Central Eastern Europe. *European Planning Studies*, *19*(9), 1669-1690. https://doi.org/10.1080/09654313.2011.586186

Giczy, A. V., Pairolero, N. A., & Toole, A. A. (2021). Identifying artificial intelligence (AI) invention: a novel AI patent dataset. *The Journal Of Technology Transfer*, *47*(2), 476-505. https://doi.org/10.1007/s10961-021-09900-2

Gofman, M., & Jin, Z. (2024). Artificial intelligence, education, and entrepreneurship. The *Journal of Finance, 79*(1), 631-667. https://doi.org/10.1111/jofi.13302

Gössling, T., & Rutten, R. (2007). Innovation in regions. *European Planning Studies*, *15*(2), 253-270. https://doi.org/10.1080/09654310601078788

Griliches, Z. (1979). Issues in Assessing the Contribution of Research and Development to Productivity Growth. *The Bell Journal Of Economics*, *10*(1), 92-116. https://doi.org/10.2307/3003321

Gupta, S. (2008). Research Note - Channel Structure with Knowledge Spillovers. *Marketing Science*, *27*(2), 247-261. https://doi.org/10.1287/mksc.1070.0285

Harris, R., & Yan, J. (2018). The measurement of absorptive capacity from an economics perspective: definition, measurement and importance. *Journal Of Economic Surveys*, *33*(3), 729-756. https://doi.org/10.1111/joes.12296

Heaton, S., Siegel, D. S., & Teece, D. J. (2019). Universities and innovation ecosystems: a dynamic capabilities perspective. *Industrial And Corporate Change*, *28*(4), 921-939. https://doi.org/10.1093/icc/dtz038

Henderson, E. F., & Burford, J. (2019). Thoughtful gatherings: gendering conferences as spaces of learning, knowledge production and community. *Gender And Education*, *32*(1), 1-10. https://doi.org/10.1080/09540253.2019.1691718

Horbach, J. (2013). Do eco-innovations need specific regional characteristics? An econometric analysis for Germany. *Review Of Regional Research*, *34*(1), 23-38. https://doi.org/10.1007/s10037-013-0079-4

Hsiao, C. (2007). Panel data analysis—advantages and challenges. *Test*, *16*(1), 1-22. https://doi.org/10.1007/s11749-007-0046-x

Igna, I. A., & Venturini, F. (2023). The determinants of AI innovation across European firms. *Research Policy*, *52*(2), 104661. https://doi.org/10.1016/j.respol.2022.104661

Jaffe, A. B. (1989). Real Effects of Academic Research. *The American Economic Review*, *79*(5), 957-970. http://www.jstor.org/stable/1831431

Jee, S. J., & Sohn, S. Y. (2023). A firm's creation of proprietary knowledge linked to the knowledge spilled over from its research publications: the case of artificial intelligence. *Industrial And Corporate Change*, *32*(4), 876-900. https://doi.org/10.1093/icc/dtad002

Jewell, C. (2019). *Artificial intelligence: the new electricity.* WIPO Magazine. Accessed on 18. February 2024 from https://www.wipo.int/wipo_magazine/en/2019/03/article_0001.html

Jiang, Y., Li, X., Luo, H., Yin, S., & Kaynak, O. (2022). Quo vadis artificial intelligence? *Discover Artificial Intelligence, 2*(1), 4-23. https://doi.org/10.1007/s44163-022-00022-8

Keller, W. (1996). Absorptive capacity: On the creation and acquisition of technology in development. *Journal of development economics, 49*(1), 199-227. https://doi.org/10.1016/0304-3878(95)00060-7

Kenney, M., & Patton, D. (2009). Reconsidering the Bayh-Dole Act and the Current University Invention Ownership Model. *Research Policy*, *38*(9), 1407-1422. https://doi.org/10.1016/j.respol.2009.07.007

Kinzius, L., Sandkamp, A., & Yalçin, E. (2019). Trade protection and the role of non-tariff barriers. *Review Of World Economics*, *155*(4), 603-643. https://doi.org/10.1007/s10290-019-00341-6

Ko, W. W., & Liu, G. (2015). Understanding the Process of Knowledge Spillovers: Learning to Become Social Enterprises. *Strategic Entrepreneurship Journal*, *9*(3), 263-285. https://doi.org/10.1002/sej.1198

Kyvik, S., & Larsen, I. M. (1994). International contact and research performance. *Scientometrics*, *29*(1), 161-172. https://doi.org/10.1007/bf02018388

Langley, P. (2019). An Integrative Framework for Artificial Intelligence Education. *Proceedings Of The AAAI Conference On Artificial Intelligence*, *33*(01), 9670-9677. https://doi.org/10.1609/aaai.v33i01.33019670

Lazzeretti, L., Domenech, R. B., Hervas-Oliver, J. L., & Innocenti, N. (2023). Artificial intelligence, big data, algorithms and Industry 4.0 in firms and clusters. *European Planning Studies, 1-7*. https://doi.org/10.1080/09654313.2023.2220490

Lecuona, J. R., & Reitzig, M. (2013). Knowledge worth having in 'excess': The value of tacit and firm-specific human resource slack. *Strategic Management Journal*, *35*(7), 954-973. https://doi.org/10.1002/smj.2143

Leten, B., Landoni, P., & Van Looy, B. (2014). Science or graduates: How do firms benefit from the proximity of universities? *Research Policy*, *43*(8), 1398-1412. https://doi.org/10.1016/j.respol.2014.03.005

Li, C., Yang, X., Zheng, H., Wang, Z., Han, H., & Zeng, L. (2023). Artificial intelligence, resource reallocation, and corporate innovation efficiency: Evidence from China's listed companies. *Resources Policy*, *81*, 103324. https://doi.org/10.1016/j.resourpol.2023.103324

Li, J., Ding, H., Hu, Y., & Wan, G. (2021). Dealing with dynamic endogeneity in international business research. *Journal Of International Business Studies*, *52*(3), 339-362. https://doi.org/10.1057/s41267-020-00398-8

Li, X. (2009). China's regional innovation capacity in transition: An empirical approach. *Research policy, 38*(2), 338-357. https://doi.org/10.1016/j.respol.2008.12.002

Liu, N., Shapira, P., & Yue, X. (2021). Tracking developments in artificial intelligence research: constructing and applying a new search strategy. *Scientometrics*, *126*(4), 3153-3192. https://doi.org/10.1007/s11192-021-03868-4

Ma, S. (2019). The Life Cycle of Corporate Venture Capital. *The Review Of Financial Studies*, *33*(1), 358-394. https://doi.org/10.1093/rfs/hhz042

Mansfield, E. (1995). Academic Research Underlying Industrial Innovations: Sources, Characteristics, and Financing. *The Review Of Economics And Statistics*, *77*(1), 55. https://doi.org/10.2307/2109992

Mason, G., Rincón-Aznar, A., & Venturini, F. (2019). Which skills contribute most to absorptive capacity, innovation and productivity performance? Evidence from the US and Western Europe. *Economics Of Innovation And New Technology*, *29*(3), 223-241. https://doi.org/10.1080/10438599.2019.1610547

McKinsey (2021). *The state of AI in 2021*. McKinsey Global Institute. Accessed on 18. February 2024 from https://www.mckinsey.com/capabilities/quantumblack/our-insights/global-survey-the-state-of-ai-in-2021

Medase, S. K. (2020). Product innovation and employees' slack time. The moderating role of firm age & size. *Journal Of Innovation & Knowledge*, *5*(3), 151-174. https://doi.org/10.1016/j.jik.2019.11.001

Meho, L. I. (2019). Using Scopus's CiteScore for assessing the quality of computer science conferences. *Journal Of Informetrics*, *13*(1), 419-433. https://doi.org/10.1016/j.joi.2019.02.006

Meléndez, A. P., Fuster, E., Lockett, N., & Del-Águila-Obra, A. R. (2020). Knowledge spillovers, knowledge filters and entrepreneurial university ecosystems. Emerging role of University-focused venture capital firms. *Knowledge Management Research, & Practice*, *19*(1), 94-105. https://doi.org/10.1080/14778238.2020.1740626

Mol, M. J., & Birkinshaw, J. (2014). The Role of External Involvement in the Creation of Management Innovations. *Organization Studies*, *35*(9), 1287-1312. https://doi.org/10.1177/0170840614539313

Moore, J. F. (1993). Predators and prey: a new ecology of competition. *Harvard business review, 71*(3), 75-86.

Müller, V., Rosenbusch, N., & Bausch, A. (2013). Success patterns of exploratory and exploitative innovation: A meta-analysis of the influence of institutional factors. *Journal of Management, 39*(6), 1606-1636. https://doi.org/10.1177/0149206313484516

Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence, 2*, 100041. https://doi.org/10.1016/j.caeai.2021.100041

Nguyen, A., Tuunanen, T., Gardner, L. A., & Sheridan, D. (2020). Design principles for learning analytics information systems in higher education. *European Journal Of Information Systems*, *30*(5), 541-568. https://doi.org/10.1080/0960085x.2020.1816144

Nie, L., Gong, H., Zhao, D., Lai, X., & Chang, M. (2022). Heterogeneous knowledge spillover channels in universities and green technology innovation in local firms: Stimulating quantity or quality? *Frontiers in Psychology*, *13*, 943655. https://doi.org/10.3389/fpsyg.2022.943655

Operti, E., & Carnabuci, G. (2014). Public knowledge, private gain: The effect of spillover networks on firms' innovative performance. *Journal of Management, 40*(4), 1042-1074. https://doi.org/10.1177/0149206311422448

Organization for Economic Cooperation and Development (2021). *State of implementation of the OECD AI Principles: Insights from national AI policies.* OECD Digital Economy Papers, 311. Accessed on 18. February 2024 from https://www.oecd.org/digital/state-of-implementation-of-the-oecd-ai-principles-1cd40c44-en.htm

Panetti, E., Parmentola, A., Ferretti, M., & Reynolds, E. B. (2019). Exploring the relational dimension in a smart innovation ecosystem: a comprehensive framework to define the network structure and the network portfolio. *The Journal Of Technology Transfer*, *45*(6), 1775-1796. https://doi.org/10.1007/s10961-019-09735-y

Ployhart, R. E., Weekley, J. A., & Ramsey, J. R. (2009). The Consequences of Human Resource Stocks and Flows: A Longitudinal Examination of Unit Service Orientation and Unit Effectiveness. *Academy Of Management Journal*, *52*(5), 996-1015. https://doi.org/10.5465/amj.2009.44635041

Power, D., & Malmberg, A. (2008). The contribution of universities to innovation and economic development: in what sense a regional problem? *Cambridge Journal Of Regions, Economy And Society*, *1*(2), 233-245. https://doi.org/10.1093/cjres/rsn006

Qiu, S., Liu, X., & Gao, T. (2017). Do emerging countries prefer local knowledge or distant knowledge? Spillover effect of university collaborations on local firms. *Research Policy*, *46*(7), 1299-1311. https://doi.org/10.1016/j.respol.2017.06.001

Rowe, N., & Ilić, D. (2009). What impact do posters have on academic knowledge transfer? A pilot survey on author attitudes and experiences. *BMC Medical Education*, *9*(1), 1-7. https://doi.org/10.1186/1472-6920-9-71

Runge, S., Schwens, C., & Schulz, M. (2021). The invention performance implications of coopetition: How technological, geographical, and product market overlaps shape learning and competitive tension in R&D alliances. *Strategic Management Journal*, *43*(2), 266-294. https://doi.org/10.1002/smj.3334

Sapci, A. H., & Sapci, H. (2020). Artificial Intelligence Education and Tools for Medical and Health Informatics Students: Systematic Review. *JMIR Medical Education*, *6*(1), e19285. https://doi.org/10.2196/19285

Schiller, D., & Diez, J. R. (2010). Local embeddedness of knowledge spillover agents: Empirical evidence from German star scientists. *Papers in Regional Science*, *89*(2), 275-294. https://doi.org/10.1111/j.1435-5957.2010.00294.x

Sharfman, M. P., Wolf, G., Chase, R. B., & Tansik, D. A. (1988). Antecedents of Organizational Slack. *Academy Of Management Review*, *13*(4), 601-614. https://doi.org/10.5465/amr.1988.4307484

Shum, S. B., & Luckin, R. (2019). Learning analytics and AI: Politics, pedagogy and practices. *British Journal Of Educational Technology*, *50*(6), 2785-2793. https://doi.org/10.1111/bjet.12880

Siedschlag, I., Smith, D., Turcu, C., & Zhang, X. (2013). What determines the location choice of R&D activities by multinational firms? *Research Policy*, *42*(8), 1420-1430. https://doi.org/10.1016/j.respol.2013.06.003

Simmie, J. (2002). Knowledge Spillovers and Reasons for the Concentration of Innovative SMEs. *Urban Studies*, *39*(5-6), 885-902. https://doi.org/10.1080/00420980220128363

Singh, J. (2008). Distributed R&D, cross-regional knowledge integration and quality of innovative output. *Research Policy*, *37*(1), 77-96. https://doi.org/10.1016/j.respol.2007.09.004

Smeby, J., & Trondal, J. (2005). Globalisation or europeanisation? International contact among university staff. *Higher Education*, *49*(4), 449-466. https://doi.org/10.1007/s10734-004-2826-5

Snee, R. D. (1973). Some aspects of nonorthogonal data analysis: Part I. Developing prediction equations. *Journal of Quality Technology, 5*(2), 67-79. https://doi.org/10.1080/00224065.1973.11980577

Sohn, E. (2021). How Local Industry R&D Shapes Academic Research: Evidence from the Agricultural Biotechnology Revolution. *Organization Science*, *32*(3), 675-707. https://doi.org/10.1287/orsc.2020.140

Stanford University (2019). *Artificial Intelligence Index Report 2019*. AI Index Steering Committee, Stanford Institute for Human-Centered AI. Accessed on 18. February 2024 from https://hai.stanford.edu/sites/default/files/ai_index_2019_report.pdf

Stanford University (2022a). *Artificial Intelligence Definitions*. Stanford Institute for Human-Centered AI. Accessed on 18. February 2024 from https://hai.stanford.edu/sites/default/files/2023-03/AI-Key-Terms-Glossary-Definition.pdf

Stanford University (2022b). *Artificial Intelligence Index Report 2022*. AI Index Steering Committee, Stanford Institute for Human-Centered AI. Accessed on 18. February 2024 from https://aiindex.stanford.edu/wp-content/uploads/2022/03/2022-AI-Index-Report_Master.pdf.

Sultana, N., Turkina, E., & Cohendet, P. (2023). The mechanisms underlying the emergence of innovation ecosystems: the case of the AI ecosystem in Montreal. *European Planning Studies*, *31*(7), 1443-1465. https://doi.org/10.1080/09654313.2023.2185502

Sun, H., Edziah, B. K., Sun, C., & Kporsu, A. K. (2019). Institutional quality, green innovation and energy efficiency. *Energy Policy*, *135*, 111002. https://doi.org/10.1016/j.enpol.2019.111002

Taddeo, M., & Floridi, L. (2018). How AI can be a force for good. *Science*, *361*(6404), 751-752. https://doi.org/10.1126/science.aat5991

Thompson, N., Ziedonis, A. A., & Mowery, D. C. (2018). University licensing and the flow of scientific knowledge. *Research Policy*, *47*(6), 1060-1069. https://doi.org/10.1016/j.respol.2018.03.008

Toivanen, O., & Väänänen, L. (2016). Education and Invention. *The Review Of Economics And Statistics*, *98*(2), 382-396. https://doi.org/10.1162/rest_a_00520

Troilo, G., De Luca, L. M., & Atuahene-Gima, K. (2013). More Innovation with Less? A Strategic Contingency View of Slack Resources, Information Search, and Radical Innovation. *Journal Of Product Innovation Management*, *31*(2), 259-277. https://doi.org/10.1111/jpim.12094

US Bureau of Economic Analysis (2024). *Interactive Data Application*. Accessed on 18. February 2024 from https://www.bea.gov/itable/

US Bureau of Labor Statistics (2024). *Local Area Unemployment Statistics*. Accessed on 18. February 2024 from https://www.bls.gov/lau/tables.htm#mcounty

US Census Bureau (2024a). *Explore Census Data*. Accessed on 18. February 2024 from https://data.census.gov

US Census Bureau (2024b). *Economic Census: NAICS Codes & Understanding Industry Classification Systems.* Accessed on 18. February 2024 from https://www.census.gov/programs-surveys/economic-census/year/2022/guidance/understanding-naics.html

US Executive Office (2019). *Maintaining American Leadership in Artificial Intelligence*. Accessed on 18. February 2024 from https://www.federalregister.gov/documents/2019/02/14/2019-02544/maintaining-american-leadership-in-artificial-intelligence

US National Center for Science and Engineering Statistics (2024). *HERD survey on R&D expenditures.* Accessed on 18. February 2024 from https://ncses.nsf.gov/surveys/higher-education-research-development/2021

USPTO (2021). *Artificial Intelligence Patent Dataset*. Accessed on 18. February 2024 from https://www.uspto.gov/ip-policy/economic-research/research-datasets/artificial-intelligence-patent-dataset

USPTO (2024a). *Patent process overview*. Accessed on 18. February 2024 from https://www.uspto.gov/patents/basics/patent-process-overview

USPTO (2024b). *Managing a patent*. Accessed on 18. February 2024 from https://www.uspto.gov/patents/basics/manage

Valero, A., & Van Reenen, J. (2019). The economic impact of universities: Evidence from across the globe. *Economics Of Education Review*, *68*, 53-67. https://doi.org/10.1016/j.econedurev.2018.09.001

Van Looy, B., Landoni, P., Callaert, J., Van Pottelsberghe, B., Sabsalis, E., & Debackere, K. (2011). Entrepreneurial effectiveness of European universities: An empirical assessment of antecedents and trade-offs. *Research Policy*, *40*(4), 553-564. https://doi.org/10.1016/j.respol.2011.02.001

Varga, A. (1998). *University Research and Regional Innovation: A Spatial Econometric Analysis of Academic Technology Transfers* (Vol. 13). Berlin: Springer Science & Business Media.

Varga, A. (2000). Local Academic Knowledge Transfers and the Concentration of Economic Activity. *Journal Of Regional Science*, *40*(2), 289-309. https://doi.org/10.1111/0022-4146.00175

Varga, A., Anselin, L., & Ács, Z. J. (2005). Regional Innovation in the US over Space and Time. In *Spillovers and Innovations*, 93-104. Vienna: Springer.

Veugelers, R. (1997). Internal R, & D expenditures and external technology sourcing. *Research Policy*, *26*(3), 303-315. https://doi.org/10.1016/s0048-7333(97)00019-x

Wang, Q., & Huang, K. W. (2021). Exploring the Heterogeneous Knowledge Spillover Effects from University AI Research on the Creation and Performance of AI Start-ups. In *14th China Summer Workshop on Information Management*, 32-37.

Wennberg, K., Wiklund, J., & Wright, M. (2011). The effectiveness of university knowledge spillovers: Performance differences between university spinoffs and corporate spinoffs. *Research Policy*, *40*(8), 1128-1143. https://doi.org/10.1016/j.respol.2011.05.014

West, J., & Bogers, M. (2013). Leveraging External Sources of Innovation: A Review of Research on Open Innovation. *Journal Of Product Innovation Management*, *31*(4), 814-831. https://doi.org/10.1111/jpim.12125

White, H. (1980). A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica*, *48*(4), 817-838. https://doi.org/10.2307/1912934

Woodward, D., Figueiredo, O., & Guimarães, P. (2006). Beyond the Silicon Valley: University R&D and high-technology location. *Journal Of Urban Economics*, *60*(1), 15-32. https://doi.org/10.1016/j.jue.2006.01.002

Wooldridge, J. M. (2001). *Econometric Analysis of Cross Section and Panel Data*. Cambridge, Massachusetts: MIT press.

World Intellectual Property Organization (2019). *WIPO Technology Trends 2019*. Accessed on 18. February 2024 from https://www.wipo.int/edocs/pubdocs/en/wipo_pub_1055.pdf

Xu, G., Wu, Y., Minshall, T., & Zhou, Y. (2018). Exploring innovation ecosystems across science, technology, and business: A case of 3D printing in China. *Technological Forecasting And Social Change*, *136*, 208-221. https://doi.org/10.1016/j.techfore.2017.06.030

Xu, J., & Babaian, T. (2021). Artificial intelligence in business curriculum: The pedagogy and learning outcomes. *The International Journal Of Management Education, 19*(3), 100550. https://doi.org/10.1016/j.ijme.2021.100550

Yaghmaie, P., & Vanhaverbeke, W. (2020). Identifying and describing constituents of innovation ecosystems: A systematic review of the literature. *EuroMed Journal of Business, 15*(3), 283-314. https://doi.org/10.1108/EMJB-03-2019-0042

Yin, K., Cai, F., & Huang, C. (2022). How does artificial intelligence development affect green technology innovation in China? Evidence from dynamic panel data analysis. *Environmental Science And Pollution Research*, *30*(10), 28066-28090. https://doi.org/10.1007/s11356-022-24088-0

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education - where are the educators? *International Journal Of Educational Technology in Higher Education*, *16*(1). https://doi.org/10.1186/s41239-019-0171-0

Zhang, C., & Lu, Y. (2021). Study on artificial intelligence: The state of the art and future prospects. *Journal Of Industrial Information Integration*, *23*, 100224. https://doi.org/10.1016/j.jii.2021.100224

Zucker, L. G., Darby, M. R., & Armstrong, J. (2002). Commercializing Knowledge: University Science, Knowledge Capture, and Firm Performance in Biotechnology. *Management Science*, *48*(1), 138-153. https://doi.org/10.1287/mnsc.48.1.138.14274

Appendix

Figure 1: Identification of private patents

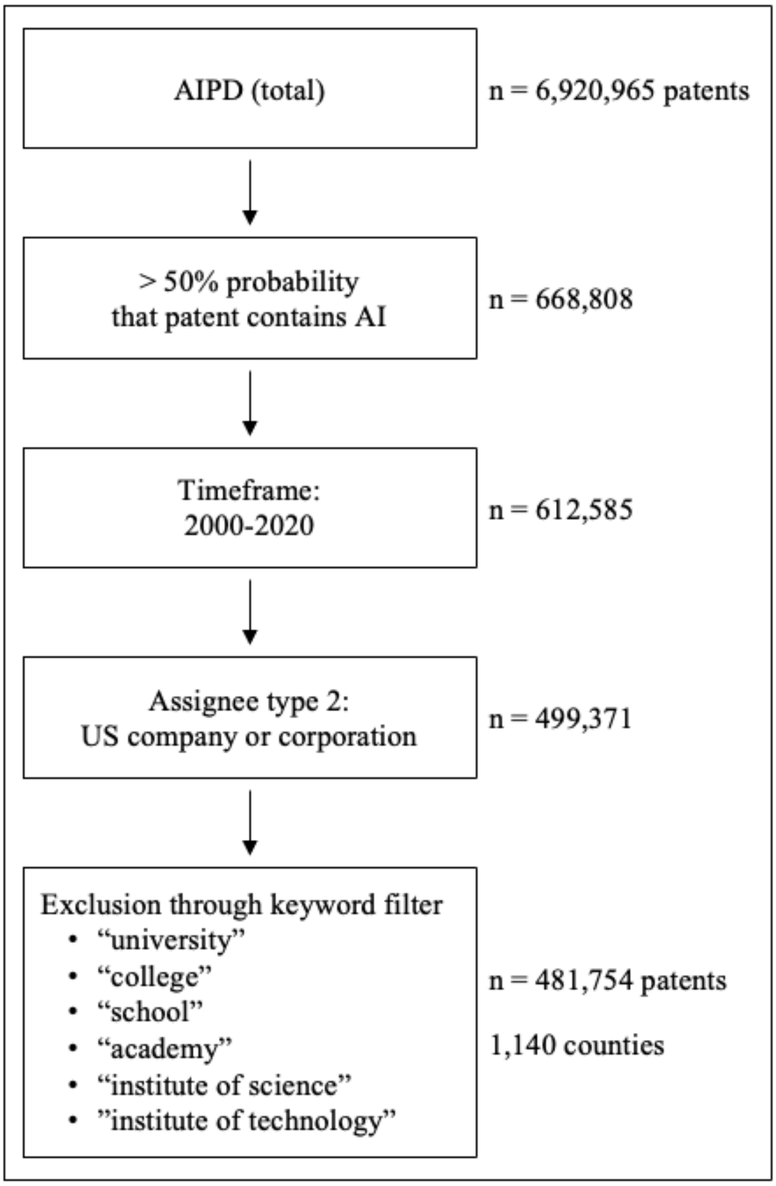
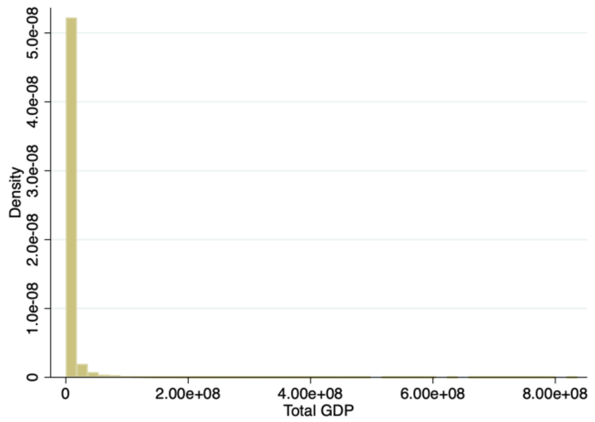


Table 1: AI conferences held in the US from 2000 to 2020

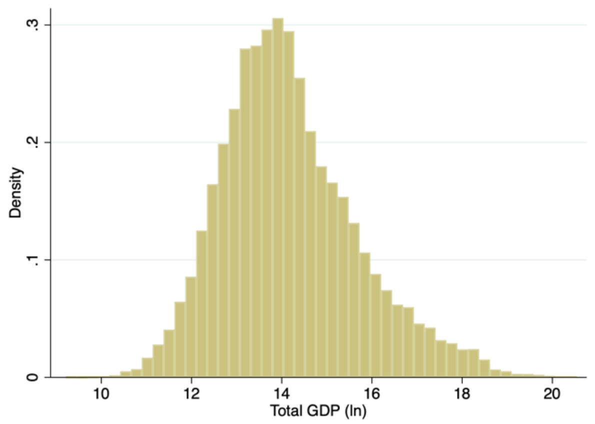
Name	No. of events
AAAI Conference on Artificial Intelligence	14
ACM Conference on Recommender Systems	5
ACM International Conference on Information & Knowledge Management	10
ACM International Conference on Web Search & Data Mining	7
ACM SIGKDD International Conference on Knowledge Discovery & Data Mining	5
ACM/IEEE Joint Conference on Digital Libraries	14
Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies	12
Conference on Empirical Methods in Natural Language Processing	4
Conference on Learning Theory	7
Conference on Natural Language Learning	6
Conference on Neural Information Processing Systems	4
Data Compression Conference	20
IEEE Conference on Computer Vision and Pattern Recognition	18
IEEE International Conference on Automatic Face & Gesture Recognition	3
IEEE International Conference on Biometrics Theory, Applications & Systems	10
IEEE International Conference on Data Mining	8
IEEE Winter Conference on Applications of Computer Vision	16
IEEE Workshop on Automatic Speech Recognition & Understanding	2
International Conference on R&D in Information Retrieval	5
International Conference on Artificial Intelligence and Statistics	7
International Conference on Automated Planning and Scheduling	5
International Conference on Computational Linguistics	1
International Conference on Document Analysis and Recognition	3
International Conference on Learning Representations	4
International Conference on Machine Learning	9
International Conference on Multimedia Retrieval	6
International Conference on the Principles of Knowledge Representation & Reasoning	2
International Conference on Uncertainty in Artificial Intelligence	8
International Joint Conference on Artificial Intelligence	3
International Joint Conference on Autonomous Agents & Multiagent Systems	5
International Semantic Web Conference	7
Meeting of the Association for Computational Linguistics	5
The Web Conference	4

Figure 2: Histogram of *Total GDP*



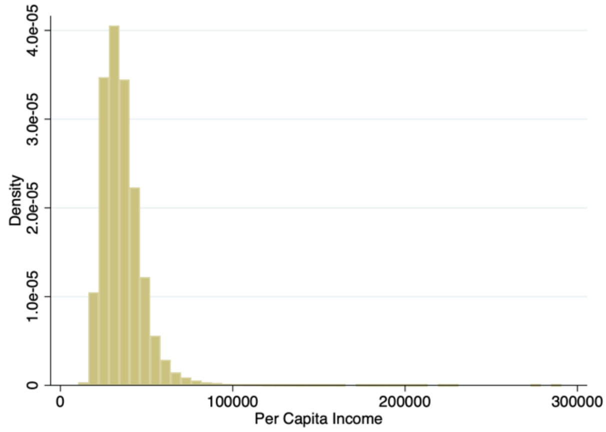
Source: Stata output

Figure 3: Histogram of Natural Logarithm of *Total GDP*



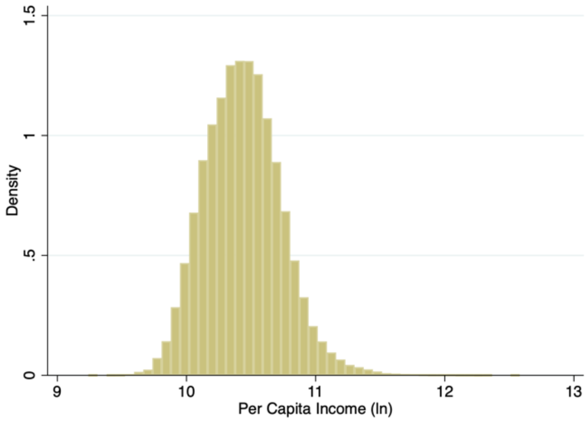
Source: Stata output

Figure 4: Histogram of *Per Capita Income*



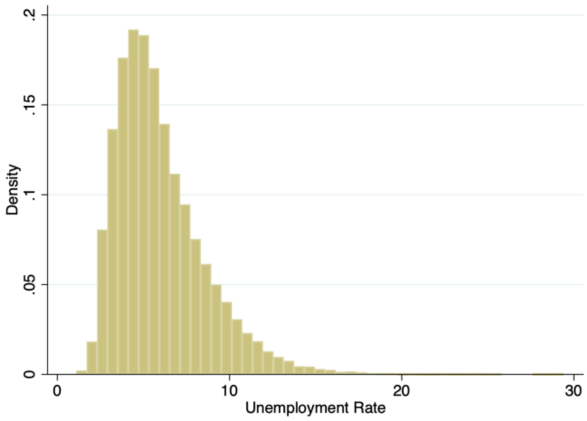
Source: Stata output

Figure 5: Histogram of Natural Logarithm of *Per Capita Income*



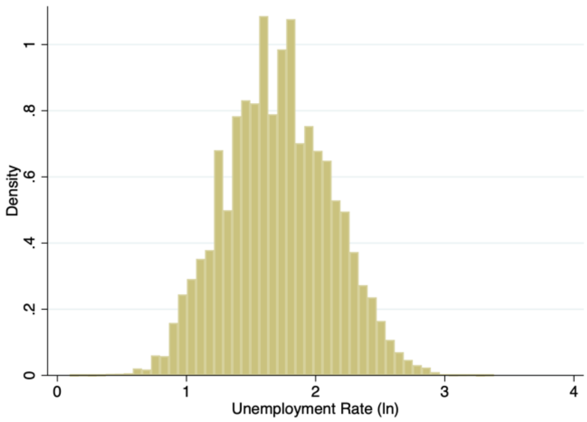
Source: Stata output

Figure 6: Histogram of *Unemployment Rate*



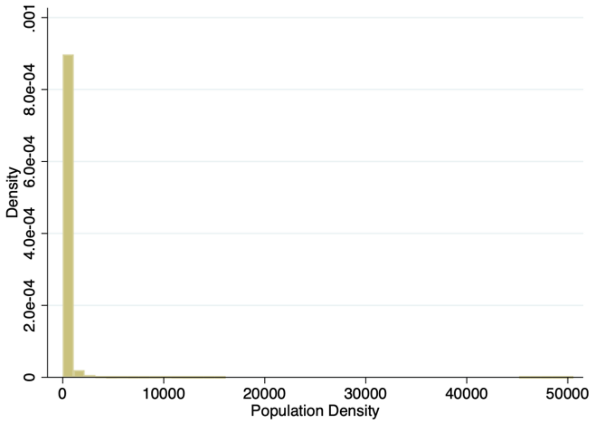
Source: Stata output

Figure 7: Histogram of Natural Logarithm of *Unemployment Rate*



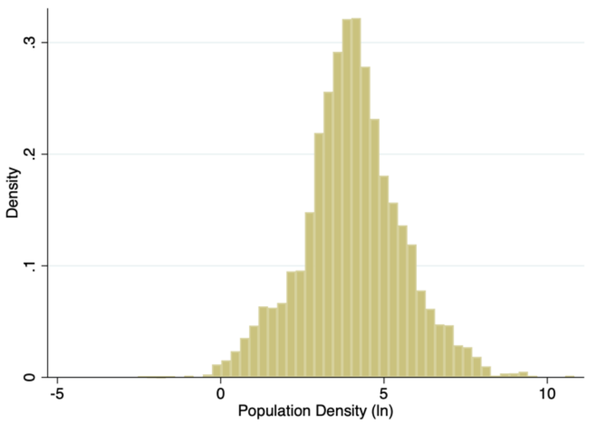
Source: Stata output

Figure 8: Histogram of *Population Density*



Source: Stata output

Figure 9: Histogram of Natural Logarithm of *Population Density*



Source: Stata output

Figure 10: Research model

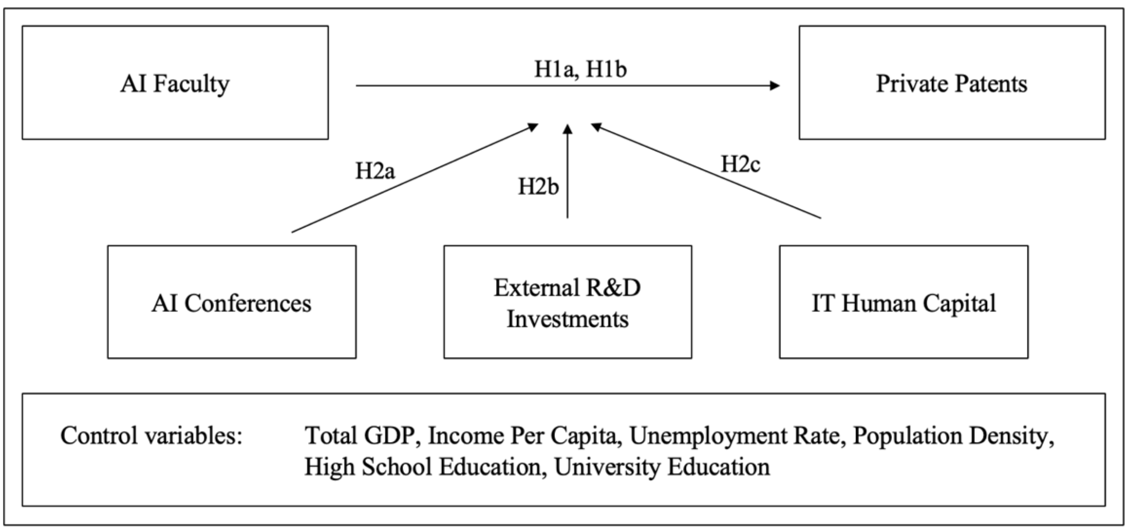


Table 2: Autocorrelation (Woolridge test)

	Main Regression	Moderation (AI Conferences)	Moderation (R&D Investment)	Moderation (Human Capital IT)
F	13.066	13.085	12.785	13.085
Prob > F	0.0003	0.0003	0.0004	0.0003

Note: H0: No first-order autocorrelation
H1: First-order autocorrelation

Table 3: Heteroscedasticity (White test)

	Main Regression	Moderation (AI Conferences)	Moderation (R&D Investment)	Moderation (Human Capital IT)
chi2	3342.03	6925.07	5159.44	10143.32
Prob > chi2	0.0000	0.0000	0.0000	0.0000

Note: H0: Homoscedasticity
H1: Unrestricted Heteroscedasticity

Table 4: Random versus fixed effects (xtoverid test)

	Main Regression	Moderation (AI Conferences)	Moderation (R&D Investment)	Moderation (Human Capital IT)
Sargan Hansen Statistic	11.169	15.708	13.004	14.598
P-value	0.1314	0.0732	0.1152	0.0972

Note: H0: Difference in coefficients not systematic
H1: Difference in coefficients systematic

Table 5: Summary statistics

	Variable	Mean	SD	Min	Max
1	Private Patents	20.12	182.93	0	8196.00
2	AI Faculty	0.56	3.18	0	88.00
3	AI Conferences (dummy)	0.03	0.16	0	1.00
4	R&D Investment	47,025.53	201,051.80	0	3,642,476.00
5	IT Human Capital	2,419.30	5,502.71	24.00	36,443.00
6	Total GDP (ln)	15.09	1.46	11.23	18.34
7	Per Capita Income (ln)	10.52	0.30	9.24	12.58
8	Unemployment Rate (ln)	1.69	0.39	0.83	2.66
9	Population Density (ln)	4.78	1.49	0.35	7.84
10	High School Education	86.93	3.92	76.00	93.40
11	University Education	28.34	5.06	17.40	40.90

Table 6: Bivariate correlations

	Variable	1	2	3	4	5	6	7	8	9	10	11
1	Private Patents	1.00										
2	AI Faculty	0.32	1.00									
3	AI Conferences (dummy)	0.17	0.35	1.00								
4	R&D Investment	0.31	0.76	0.36	1.00							
5	IT Human Capital	0.39	0.50	0.42	0.59	1.00						
6	Total GDP (ln)	0.20	0.29	0.26	0.35	0.66	1.00					
7	Per Capita Income (ln)	0.20	0.20	0.17	0.23	0.32	0.47	1.00				
8	Unemployment Rate (ln)	-0.02	-0.02	-0.01	-0.02	-0.05	-0.02	-0.21	1.00			
9	Population Density (ln)	0.16	0.24	0.20	0.29	0.55	0.83	0.31	-0.01	1.00		
10	High School Education	-0.02	0.01	0.00	-0.01	-0.09	-0.03	0.39	-0.15	-0.14	1.00	
11	University Education	0.09	0.14	0.10	0.12	0.12	0.21	0.51	-0.07	0.11	0.50	1.00

Table 7: VIFs

	Variable	Main Regression	Moderator: AI Conferences	Moderator: R&D Investment	Moderator: IT Human Capital
1	AI Faculty	1.11	1.87	3.99	1.85
2	AI Conferences (dummy)		1.50		
3	R&D Investment			2.90	
4	IT Human Capital				2.34
5	Total GDP (ln)	3.85	3.91	3.97	4.43
6	Per Capita Income (ln)	1.88	1.88	1.89	1.88
7	Unemployment Rate (ln)	1.06	1.07	1.06	1.07
8	Population Density (ln)	3.32	3.32	3.32	3.13
9	High School Education	1.53	1.53	1.53	1.54
10	University Education	1.60	1.61	1.61	1.61
	Mean VIF	2.05	2.10	2.70	2.79

Table 8: Impact of *AI Faculty* on *Private Patents*

	Model 1			Model 2			Model 3[a]			Model 4[b]			Model 5[c]		
Variables	B	SE	*p*	B	SE	*p*	B	SE	*p*	B	SE	*p*	B	SE	*p*
Constant	-736.46	408.33	0.07	-572.04	345.87	0.10	-205.29	193.87	0.29	-29.92	194.38	0.88	45.79	247.73	0.85
AI Faculty				17.82	7.22	0.01	23.37	9.79	0.02	23.86	9.29	0.01	25.33	10.39	0.02
Total GDP (ln)	-52.08	28.82	0.07	-39.20	21.65	0.07	-30.36	17.83	0.09	-21.24	14.46	0.14	-15.83	11.83	0.18
Per Capita Income (ln)	150.85	79.67	0.05	120.05	64.08	0.04	76.26	40.38	0.05	46.21	23.67	0.05	29.56	16.26	0.07
Unemployment Rate (ln)	-0.96	11.81	0.94	-3.99	12.26	0.75	-4.86	9.69	0.62	-3.23	7.89	0.68	-0.27	6.16	0.96
Population Density (ln)	52.72	23.53	0.03	35.88	15.25	0.02	31.52	13.36	0.02	27.24	12.11	0.02	24.81	10.34	0.02
High School Education	-4.06	1.74	0.02	-3.31	1.42	0.02	-3.67	1.50	0.01	-3.62	1.56	0.02	-3.30	1.53	0.03
University Education	2.35	1.33	0.08	1.43	1.35	0.29	1.45	1.35	0.28	1.91	1.26	0.13	1.83	1.05	0.08
Interaction AI Faculty x AI Conferences															
Interaction AI Faculty x R&D Investment															
Interaction AI Faculty x IT Human Capital															
Year dummies	Yes			Yes			Yes			Yes			Yes		
R-squared (within)	0.0307			0.1089			0.1048			0.0868			0.0813		
Wald Chi^2	85.99			107.91			83.01			99.69			93.33		
No. of groups	1,139			1,139			1,139			1,139			1,139		
No. of observations	23,911			23,940			20,494			18,216			15,946		

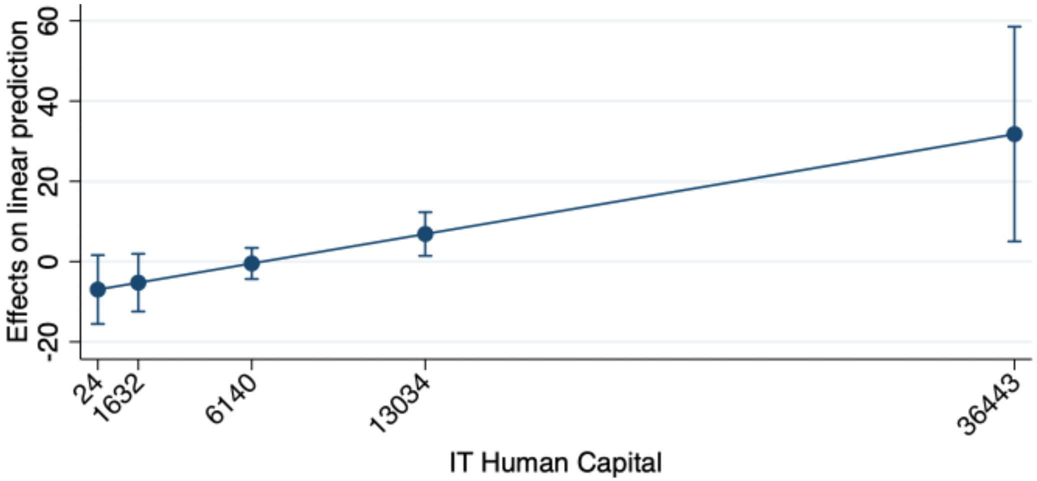
Note: Random effects panel regression with clustered standard errors (clustered at the county level).
[a] Time lag of 3 years for variable *AI Faculty*.
[b] Time lag of 5 years for variable *AI Faculty*.
[c] Time lag of 7 years for variable *AI Faculty*.

Table 8: Impact of *AI Faculty* on *Private Patents* (continued)

	Model 6[a]			Model 7			Model 8			Model 9		
Variables	B	SE	*p*	B	SE	*p*	B	SE	*p*	B	SE	*p*
Constant	234.14	327.33	0.47	-574.42	345.75	0.10	-539.22	336.78	0.11	-441.80	369.41	0.23
AI Faculty	13.41	6.68	0.02	19.22	8.78	0.03	13.43	10.86	0.21	-6.99	4.38	0.11
Total GDP (ln)	-3.30	8.02	0.68	-39.30	21.48	0.07	-39.91	23.65	0.09	-27.16	19.73	0.17
Per Capita Income (ln)	-8.61	17.84	0.63	120.27	63.64	0.05	119.46	65.60	0.07	95.50	53.75	0.08
Unemployment Rate (ln)	0.46	4.11	0.91	-3.88	12.09	0.75	-3.99	12.35	0.75	-2.15	11.95	0.86
Population Density (ln)	19.13	8.24	0.02	36.24	15.63	0.02	32.09	14.95	0.03	23.31	10.20	0.02
High School Education	-2.72	1,47	0.06	-3.35	1.45	0.02	-3.32	1.42	0.02	-3.50	1.40	0.01
University Education	1.76	0.77	0.02	1.54	1.31	0.24	1.37	1.37	0.32	1.87	1.35	0.17
Interaction AI Faculty x AI Conferences				-3.98	5.40	0.46						
Interaction AI Faculty x R&D Investment							0.00	0.00	0.80			
Interaction AI Faculty x IT Human Capital										0.01	0.00	0.03
Year dummies	Yes			Yes			Yes			Yes		
R-squared (within)	0.0735			0.1147			0.1212			0.1718		
Wald Chi^2	90.79			168.90			150.95			150.95		
No. of groups	1,139			1,139			1,139			1,133		
No. of observations	13,668			23,911			23,911			22,876		

Note: Random effects panel regression (standard errors clustered at the county level).
[a] Time lag of 9 years for variable *AI Faculty*.

Figure 11: Marginal effects of *IT Human Capital* on *AI Faculty* and *Private Patents*



Source: Stata output

Table 9: Marginal effects of *IT Human Capital* on *AI Faculty* and *Private Patents*

Percentile	Value *IT Human Capital*	dy/dx	SE	*p*	95% confidence interval	
1st	24	-6.97	4.38	0.11	-15.54	1.61
5th	48	-6.94	4.36	0.22	-15.50	1.61
10th	79	-6.91	4.35	0.11	-15.44	1.62
25th	182	-6.80	4.30	0.11	-15.24	1.64
50th	520	-6.44	4.15	0.12	-14.58	1.70
75th	1632	-5.26	3.67	0.15	-12.44	1.93
90th	6140	-0.46	1.98	0.81	-4.34	3.41
95th	13034	6.87	2.77	0.01	1.43	12.30
99th	36443	31.77	13.65	0.02	5.01	58.53

Table 10: Robustness checks

Variables	Model R1[a]			Model R2[b]			Model R3[c]			Model R4[d]		
	B	SE	*p*	B	SE	*p*	B	SE	*p*	B	SE	*p*
Constant	-319.53	329.01	0.33	-22.48	0.90	0.00	-561.20	345.11	0.10	-828.67	538.28	0.12
AI Faculty	17.31	6.93	0.01	0.02	0.00	0.00	17.82	7.22	0.01	42.92	16.71	0.01
Total GDP (ln)	-102.67	52.05	0.05	0.96	0.02	0.00	-40.65	22.34	0.07	104.74	161.74	0.51
Per Capita Income (ln)	148.71	83.63	0.08	0.37	0.08	0.00	120.52	64.55	0.06	108.16	73.86	0.14
Unemployment Rate (ln)	-13.98	16.13	0.39	-0.22	0.05	0.00	-4.25	12.35	0.73	219.08	133.23	0.10
Population Density (ln)	128.60	58.08	0.03	0.00	0.03	0.90	37.18	15.85	0.02	-212.93	120.47	0.08
High School Education	-3.82	1.61	0.02	0.02	0.01	0.00	-3.31	1.42	0.02	-44.84	20.38	0.03
University Education	1.77	1.70	0.30	0.05	0.00	0.00	1.45	1.37	0.29	-5.75	27.92	0.84
Year dummies	Yes			Yes			Yes			Yes		
R-squared (within)	0.1130			-			-			0.5775		
Wald Chi^2	-			11,381.45			108.22			183.44		
No. of groups	1,139			1,139			1,139			50		
No. of observations	23,911			23,911			23,911			1,050		

Note: [a] Fixed effects panel regression (standard errors clustered at the county level).
[b] Negative binomial regression (standard errors clustered at the county level).
[c] GEE regression (standard errors clustered at the county level).
[d] Random effects panel regression (standard errors clustered at the state level).

Table 10: Robustness checks (continued)

Variables	Model R5[a] B	SE	*p*	Model R6[b] B	SE	*p*	Model R7[c] B	SE	*p*	Model R8[d] B	SE	*p*
Constant	-733.23	407.03	0.07	75.07	135.99	0.58	-154.99	596.29	0.01	-189.28	298.87	0.53
AI Faculty	15.19	7.07	0.03	13.26	6.48	0.04	9.33	4.23	0.03	13.82	4.78	0.00
Total GDP (ln)	-52.22	28.80	0.07	-2.27	2.97	0.44	-34.65	19.00	0.07	-374.35	192.35	0.52
Per Capita Income (ln)	150.98	79.55	0.06	1.30	9.46	0.89	186.28	85.72	0.03	778.22	588.63	0.19
Unemployment Rate (ln)	-0.64	11.71	0.96	0.06	3.50	0.99	9.81	8.49	0.25	-93.31	76.47	0.22
Population Density (ln)	51.89	23.16	0.03	6.93	2.27	0.00	39.64	14.32	0.01	253.57	112.63	0.02
High School Education	-4.06	1.74	0.02	-1.22	0.52	0.02	-1.80	1.65	0.29	-17.11	8.79	0.05
University Education	2.31	1.32	0.08	0.64	0.37	0.09	2.15	1.16	0.07	-1.10	7.20	0.88
Year dummies	Yes			Yes			Yes			Yes		
R-squared (within)	0.0304			0.0690			0.0624			0.2420		
Wald Chi^2	86.46			64.21			78.55			98.93		
No. of groups	1,139			1,139			1,139			143		
No. of observations	23,911			12,529			11,390			3,003		

Note: Random effects panel regression (standard errors clustered at the county level).
[a] *AI Faculty* treated as a dummy (= 1 if *AI Faculty* > 0, = 0 otherwise).
[b] Subsample: years 2000-2010.
[c] Subsample: years 2011-2020.
[d] Subsample: counties with at least one AI faculty between 2000-2020.