

Beyond Economic Growth: Exploring the Environmental Impact of University-Industry Collaboration on Regional Low Carbon Innovation Performance

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Abstract

Climate change and ecological challenges are among humanity's most pressing issues. These challenges require collaborative efforts between the university and industrial enterprises to develop solutions that can help reduce the impact of climate change on the environment and promote sustainable development. However, the impact of these University-Industrial (U-I) collaborations on regional low-carbon innovation performance has received limited attention. To bridge this gap, our study investigates the influence of U-I knowledge creation and commercialization on regional green innovation in China, utilizing panel data from 31 provinces between 2008 and 2017. Our research advances the Regional Innovation System theory by integrating the low-carbon concept into the Regional Innovation System framework and enhancing our comprehension of the link between U-I collaboration and low-carbon innovation. We have also identified two moderation factors: the absorptive capacity of industrial enterprises and the level of digitization in a region. Our findings challenge the prevalent perspective on the significance of industrial enterprises' absorptive capacity in Regional Innovation System theory and Knowledge Management theory, revealing that the moderating role of industrial enterprises' absorptive capacity in a region on the relationship between U-I knowledge creation and regional low-carbon innovation performance is not universal.

Key words: U-I Collaboration, Absorptive Capacity, Digitization Level, Low Carbon Innovation Performance

1. Introduction

The importance of collaboration between universities and industrial enterprises (U-I) in promoting regional innovation performance has been widely recognized by scholars (e.g., Petruzzelli, 2011; Pacheco et al., 2018; Rantala and Ukko, 2019). However, recent research has raised concerns about the potential environmental consequences of innovation and research and development activities (Barbieri et al., 2020). In this context, the concepts of regional innovation performance and regional low-carbon innovation performance are of particular interest (Markard et al., 2012; Kivimaa and

Kern, 2016; Lember et al., 2016). While the former focuses on overall economic growth and innovation in a region, the latter is concerned with promoting sustainable development and reducing carbon emissions (Hertog and Staber, 2006; Uyarra et al., 2014; Zhang and Li 2019). Despite the growing interest in low-carbon innovation, it remains unclear whether U-I collaboration can lead to improvements in this area. This paper aims to fill this research gap by examining the impact of U-I collaboration on low-carbon innovation performance. Additionally, given the urgency of addressing climate change, it is essential to incorporate the concept of low carbon into the Regional Innovation System theory to ensure that low-carbon innovation is developed and implemented responsibly.

It is customary in the previous literature to classify U-I collaboration as either U-I knowledge creation or U-I knowledge commercialisation (Camisón and Villar-López, 2020; Li et al., 2020; Damanpour and Aravind, 2021). U-I knowledge creation is the process by which knowledge is generated through interactions between universities and industry and is often driven by joint research and development activities (Caloghirou et al., 2004; Chesbrough et al., 2006). On the other hand, U-I knowledge commercialization refers to the process by which universities and industry collaborate to bring new products, services or processes to the market (Siegel et al., 2007; Rasmussen et al., 2011). However, there are still gaps in our understanding of the specific mechanisms by which U-I knowledge creation and U-I knowledge commercialization contribute to regional low-carbon innovation performance, as well as the role of regional innovation system theory in this context. Thus, there is a need for more empirical research to explore the impact of different types of U-I collaboration (e.g., U-I knowledge creation and U-I knowledge commercialisation), as well as the factors that moderate the impact of different types of U-I collaborations in promoting regional low-carbon innovation (Gargiulo and Garofoli, 2017).

The collaboration between U-I knowledge creation and commercialisation is considered to involve a process of knowledge spillover (Li et al., 2020; Alavi et al., 2020; Bozeman and Boardman, 2019; Li et al., 2019). The concept of knowledge spillover refers to the transfer of knowledge from one entity to another through different channels (D'Este et al., 2013; Messeni and Murgia, 2020). The process of knowledge spillover in U-I collaboration is moderated by two important factors: the regional

absorptive capacity of industrial enterprises and the regional digitization level (Higón, 2012; Audretsch et al., 2021; Marra et al., 2022). The regional absorptive capacity of industrial enterprises refers to their ability to recognize and use external knowledge, the regional digitization level refers to the level of digital infrastructure in a region (Cooke et al., 1997; Roper and Love, 2006; Wang et al., 2020). Existing research has shown that firms with higher absorptive capacity are more likely to benefit from knowledge spillovers and that such spillovers can lead to increased innovation performance (Rothaermel and Hess, 2007; Laursen and Salter, 2006). Meanwhile, the role of digital technologies in facilitating knowledge spillover and transaction has been well documented in the literature, with studies showing that digitization can enhance the speed and efficiency of knowledge transfer (Cohen and Levinthal, 1990; Bruneel et al., 2010). Despite these insights, there are still gaps in our understanding of how the regional absorptive capacity of industrial enterprises and the regional digitization level impact U-I collaboration in promoting regional low-carbon innovation performance. For instance, it is unclear how these factors affect the different modes of U-I collaboration (e.g., U-I knowledge creation and U-I knowledge commercialisation). Thus, there is a need to explore how these moderation factors interact with U-I knowledge creation and U-I knowledge commercialisation, to shape the impact of different U-I collaboration modes on regional low-carbon innovation performance.

This study draws upon RIS theory and Knowledge Management (KM) theory (Cooke et al., 1998; Iammarino, 2005). RIS theory has been used to analyse the mechanisms and actors that facilitate innovation and competitiveness at the regional level. RIS theory emphasizes the role of local institutions, organizations, and actors in shaping the process of innovation. The key elements of RIS theory are the interactions between different actors, such as firms, universities or research centres, and the factors that support and regulate these interactions, such as absorptive capacity and digitization level in a region. The existing RIS theory does not explicitly account for low-carbon innovation, which is crucial for promoting sustainable development in the face of growing environmental and climate concerns (Cooke, 2010; Markard et al., 2012; Dameri and Rosenthal, 2022). Therefore, it is imperative to incorporate the concept of low-carbon innovation into RIS theory to ensure that innovation contributes to sustainable development and makes innovation more responsible. KM Theory is an important framework that can be used to analyse the knowledge creation and

commercialization process in U-I collaboration (Wang et al., 2020; Yang et al., 2020). According to the KM theory, knowledge creation occurs through a process of knowledge conversion, which involves socialization, externalization, combination, and internalization (Chen and Chang, 2013; Perkmann et al., 2013). This process can be facilitated by collaboration between universities and industrial enterprises, as it provides a platform for knowledge exchange and learning (Youtie and Shapira, 2008). Furthermore, the regional industrial enterprise's absorptive capacity and regional digitization level can act as moderation factors in the knowledge spillover and transaction process, impacting the effectiveness of U-I collaboration on regional low-carbon innovation performance (Huang et al., 2020; Chen et al., 2021). While the KM theory provides a useful framework to understand the U-I knowledge creation and commercialization process, there is a lack of research on the role of the regional industrial enterprise's absorptive capacity and regional digitization level as moderators of this process in the context of regional innovation systems. Further research is needed to explore these relationships and to develop more effective strategies to support U-I collaboration and regional low-carbon innovation performance.

Our study makes four contributions to the theory and low carbon innovation literature. First, our research advances RIS theory by incorporating the concept of low-carbon innovation. On this basis, our study further suggests the concept of a Regional Low-Carbon Innovation System (RLCIS). As an emerging research area, only a few studies (e.g., Yin et al., 2019) have mentioned the concept of RLCIS, and our study aims to provide more empirical evidence for RLCIS and promote its development. This is a crucial step towards achieving global sustainability goals and making innovation more responsible. Second, the study also challenges the dominant view regarding the importance of industrial enterprises' absorptive capacity in RIS and KM theories. Our findings show that the moderation role of the absorptive capacity of industrial enterprises in a region on the relationship between U-I knowledge creation and regional green innovation performance is not universal. Although previous studies (e.g., Caloghirou et al., 2004; Laursen and Salter, 2006) have emphasized the importance of absorptive capacity, our findings suggest that this may not always be the case, particularly in the context of low-carbon innovation. Third, our research further enriches the low-carbon innovation literature by providing empirical evidence for the positive moderation role of the regional digital level on the relationship between U-I

collaboration and regional low-carbon innovation performance. Our conclusion indicates that the digital level of a region can facilitate the effectiveness of U-I collaboration in promoting low-carbon innovation performance in the context of emerging economies. Finally, the study provides new insights into the contradictory assertions in the literature on the relationship between low-carbon development and innovation. By providing theoretical arguments and empirical evidence, emphasizes the role of universities and industrial enterprises in developing and implementing low-carbon technologies and innovation activities. These insights have important implications for policymakers and practitioners who seek to promote regional innovation and development.

The paper is structured as follows. Section 2 presents a review of the relevant literature and outlines the hypotheses for empirical testing. In Section 3, we describe the dataset and the regression model specification, including an explanation of the estimation methodology. We also provide a summary of how the dependent and explanatory variables are operationalized and present some descriptive statistics. The results of the regression analysis and the robustness checks are presented and discussed in Section 4. Finally, in the concluding section, we summarize the findings of the study, discuss the practical implications, and highlight any limitations of the study.

2. Literature review and hypothesis development

The regional nature of innovation activities is the subject of RIS theory (Li et al., 2016; Wang et al., 2020). The previous study defines RIS as systems in which firms and other organizations are systematically engaged in interactive learning through an institutional milieu characterized by embeddedness (Cooke et al., 1998: 1546). This applies particularly to universities and industrial enterprises within RIS (Cooke, 1992; Nelson, 1993; Freeman, 1995; Asheim et al., 2011; Li et al., 2016; Wang et al., 2020). Iammarino (2005: 499) adds that RIS constitute the localised network of various actors and institutions in different sectors whose activities and interactions generate, absorb, and diffuse new technologies within and outside the region. To incorporate the low-carbon concept into RIS theory, our study suggests the concept of the Regional Low Carbon Innovation System (RLCIS). RLCIS refers to the set of institutions, organizations, and actors that facilitate the development, diffusion, and adoption of low-carbon technologies and practices in a region. This concept acknowledges the

importance of environmental sustainability and the need to reduce carbon emissions to mitigate climate change. The key elements of RLCIS are similar to RIS, but with a focus on low-carbon technology, such as the knowledge of carbon emission reduction, and technologies for sustainable development.

In the context of U-I collaboration, RLCIS theory emphasizes the role of universities and industrial enterprises in developing and implementing low-carbon technologies and practices. The collaboration between these two actors can facilitate the transfer of low-carbon knowledge, skills, and technology from universities to firms, and from firms to universities (Camisón, C., & Villar, 2020; Messeni et al., 2020). This collaboration can also create opportunities for joint research and development projects, the commercialization of new low-carbon technologies, and the training of a skilled workforce (Liu et al., 2021). In our study, we suppose that the effectiveness of U-I collaboration for promoting RLCIS is contingent on several factors, such as the type of collaboration (e.g., U-I knowledge creation or U-I knowledge commercialisation), regional absorptive capacity, and level of local infrastructure (i.e., digital infrastructure).

In short, incorporating low-carbon into RIS theory has expanded the concept of innovation beyond economic performance to include environmental sustainability (Cao et al., 2021). The concept of RLCIS emphasizes the importance of developing and implementing low-carbon technologies and practices to mitigate climate change and promote sustainable development. In the context of U-I collaboration, RLCIS theory highlights the role of universities and industrial enterprises in facilitating the low-carbon innovation performance development and diffusion of low-carbon technologies and practices in a region.

As an effective way of knowledge diffusion, the nature of U-I knowledge creation and U-I knowledge commercialisation is the subject of KM theory. Blackler (1993), Shaw and Williams (2009) argued that KM aims to identify, select, manage, share and disseminate information to improve the knowledge for problem-solving, strategic planning and enhancing the organizational intellectual capital value. Li et al., (2016) argue that industrial enterprises trying to address their disadvantages on the knowledge identify, select, management and application when undertaking knowledge creation activities with universities. Meanwhile, Rui and Yip (2008) assert that knowledge

commercialisation are often used by industrial enterprises to acquire market assets to compensate for their competitive disadvantages, while simultaneously leveraging their own distinctive ownership advantages. Furthermore, the essence of U-I knowledge creation and U-I knowledge commercialisation is the absorptivity of knowledge (Chen and Wei, 2008). Others have also found that universities during the collaboration activities are primarily transferring knowledge, and the principal of industrial enterprises in this context is the capability to grasp the knowledge from university (Bekkers and Freitas, 2008). Hence, our study introduces the first moderation factor -- the absorptive capacity of industrial enterprises in a region. It is also worth noting that knowledge becomes relevant for the RIS only when it is really diffused to the industrial enterprises in the home region that are able to absorb it for their green innovation activities (Andersson and Karlsson, 2006). Thus, KM theory is particularly appropriate when examining the determinants of green innovation performance in the context of cross-organizational KM (Capó-Vicedo 2011; Barley et al., 2018; Flor et al., 2018).

Existing literature suggests that the extent to which U-I knowledge creation and U-I knowledge commercialisation can take place is influenced by the regional digitisation level (Nguyen and Burgess, 2014; Lorenz et al., 2020). The success of U-I collaborations depends on the ability of industrial enterprises to find appropriate partners and access the necessary knowledge within a reasonable timeframe, and their ability to understand and use that knowledge (Müller et al., 2021). Digital infrastructure facilitates the electronic storage, search, access, delivery, and retrieval of information, and supports collaboration and communication between different organisations for the gathering and processing of knowledge and information (Higón, 2012; Ollo and Aramendía, 2012; Hamad, 2018). Studies suggest that highly developed digital infrastructure is crucial in supporting industrial enterprises to absorb knowledge from external sources and accelerate the process of distribution and dissemination (Lorenz et al., 2020). Therefore, our study introduces the regional digitisation level as a second moderating factor.

The backbone of the study is an integrated conceptual framework for analysing the impact of U-I knowledge creation and U-I knowledge commercialisation on the regional low-carbon innovation performance based on ideas from two theories: The RIS focuses on interactions between organisations (e.g., U-I knowledge creation and U-I

knowledge commercialisation), spanning the public and private sectors. The absorptive capacity of industrial enterprises and regional digitization level represents the power that promotes knowledge transfer and management across organisation boundaries (Bjerregaard, 2010; Rajalo and Vadi, 2017; Sjöo et al., 2019). Thus, those theory equips us with appropriate instruments for analysing the influential essences of U-I knowledge creation and U-I knowledge commercialisation on regional green innovation performance (Blackler, 1993; Carayannis et al., 2000; Shi et al., 2020; Caloghirou et al., 2021). Combined they offer a renewed perspective for studying the impact of U-I knowledge creation and U-I knowledge commercialisation on regional green innovation performance, enabling fresh results and outcomes to provide solid conclusions for incorporating Low-carbon into RIS theory and developing the RLCIS concept.

2.1 U-I knowledge creation and regional low carbon innovation performance

Previous studies have emphasized the importance of U-I knowledge creation within the context of the RIS theory for promoting regional innovation and economic growth (Laranja et al., 2008; Li et al., 2016; Di Maria et al., 2019; Shi et al., 2020). The RIS theory highlights the significance of regional knowledge networks and interactions among various stakeholders, including universities and industrial enterprises, in fostering innovation (Cooke et al., 1997). Specifically, U-I knowledge creation can facilitate the transfer of scientific and technological knowledge from universities to industrial enterprises, thereby contributing to the development of new products and processes (Carayannis et al., 2000). However, the RIS theory does not address low-carbon innovation, which is crucial for promoting sustainable development. Thus, our study aims to explore the role of U-I knowledge creation in enhancing regional low-carbon innovation performance. We introduce the concept of low-carbon innovation into the RIS theory and thus develop the RLCIS concept. The RLCIS framework expands on the RIS theory by focusing on the development of low-carbon innovation and technologies to promote sustainable development (Berkhout et al., 2010).

In the RLCIS framework, U-I knowledge creation plays a critical role in helping industrial enterprises acquire expertise related to low-carbon innovation from universities, which can further promote low-carbon innovation performance (Messeni and Murgia, 2020). For instance, GoldWind Co Ltd, a prominent low-carbon energy

company in China, collaborated with Xinjiang University to benefit from knowledge spillovers in electricity control, leading to the development of low-carbon technologies (Zhou and Tang, 2020). Thus, U-I knowledge creation can significantly enhance regional low-carbon innovation performance, as industrial enterprises can learn from universities about emerging low-carbon technologies and their potential benefits (Lau and Lo, 2015). Therefore, it is reasonable to suppose that U-I knowledge creation can have a significant impact on regional low-carbon innovation performance, as industrial enterprises can learn from universities about emerging low-carbon technologies and the potential benefits of adopting such innovations.

H1 The U-I knowledge creation have positive impact on the low carbon regional innovation performance.

2.2 U-I knowledge commercialisation and regional low carbon innovation performance

The concept of U-I knowledge commercialisation has been extensively explored in the literature on RIS theory. Many authors suggest that one of the primary ways to promote innovation performance is through the commercialisation of technologies and research outcomes. U-I knowledge commercialisation involves the university's deliberate pursuit of commercialisation or outward transfer of its technological knowledge to industrial enterprises to obtain monetary or non-monetary benefits (Becker and Dietz, 2004; Di Maria et al., 2019). Some studies have shown that U-I knowledge commercialisation, such as knowledge transfer, patent or IP acquisition, and knowledge sharing, generates significant innovative returns in terms of profitability (Mukhtarova et al., 2016), which in turn provides substantial funds for R&D to develop new knowledge (Ramaciotti and Rizzo, 2015; Slavtchev and Göktepe-Hultén, 2016). Similarly, the concept of a regional low-carbon innovation system (RLCIS) was introduced as an extension of RIS theory to emphasise the importance of integrating low-carbon innovation into regional innovation systems to promote sustainable development. It has been suggested that universities perform most of the basic research for understanding the underlying low-carbon technology principles, while industrial enterprises focus their business capabilities on further commercialisation (Andersen, 2008). For example, industrial enterprises are the primary buyers of patenting, licensing, and scientific reports from universities (Zhou and Tang, 2020). Hence, it is reasonable to assume that U-I knowledge commercialisation catalyses investment in low-carbon

innovation, which underpins sustainable growth and promotes low-carbon innovation in a region.

Some previous studies have suggested that U-I commercialisation is a prime example of generating academic impact on low-carbon innovation development because it immediately and measurably accepts the research output from the university. In such cases, universities collaborate with industrial enterprises to conduct knowledge commercialisation, such as contracting with industrial enterprises to transfer advanced knowledge (Munari et al., 2016). However, as low-carbon domains are still in their infancy, the best environmental practices and knowledge commercialisation paradigms are yet to be established (Di Maria et al., 2019). The superiority of green technologies may not be evident for commercialisation, such as the higher development and production costs, which may reduce industrial enterprises' willingness to launch low-carbon innovation projects (Di Maria et al., 2019). Given this, this study anticipates that the impact of U-I knowledge commercialisation on regional low-carbon innovation performance is positive but less than that of U-I knowledge creation. Knowledge creation is driven by cultures that emphasise scientific performance unrelated to profit or market considerations, while knowledge commercialisation is necessary for industrial enterprises' goal of low-carbon innovation returns (Dangelico et al., 2013; Di Maria et al., 2019). We thus hypothesise:

H2 U-I knowledge commercialisation positively impacts regional low-carbon innovation performance, but to a lesser extent than U-I knowledge creation.

2.3 Absorptive capacity and regional low carbon innovation performance

The concept of absorptive capacity refers to an industrial enterprise or economy's ability to recognize the value of external information, assimilate it, and apply it to commercial ends (Gluch et al., 2009; Li, 2011). This concept applies not only to industrial enterprises but also to national or regional (Spithoven et al., 2010; Chalmers and Balan-Vnuk, 2013; Ferreras et al., 2019). Absorptive capacity directly influences the organization and implementation of knowledge management during low carbon innovation activities (Fu, 2008; Yang, 2022). Enterprises with a strong absorptive capacity are more likely to collaborate with different academic units using more frequent and penetrating methods of cooperation (Li, 2011; Zhang et al., 2020), such as

U-I knowledge creation and U-I knowledge commercialisation. it is reasonable to suppose that the absorptive capacity of industrial enterprises in a region may be directly associated with regional low carbon innovation performance

Furthermore, our study posits that the absorptive capacity of industrial enterprises will positively moderate the relationship between U-I knowledge creation and regional low carbon innovation performance. The absorptive capacity of industrial enterprises is the foundation for U-I knowledge creation and may influence the quality of R&D cooperation (Ferrerias et al., 2019). According to Zhang et al. (2020), an enterprise with a strong absorptive capacity collaborates more easily with universities during its innovative activities. The development of absorptive capacity provides an initial impulse that pushes the enterprise to keep learning and mobilize internal and external resources (Flor et al., 2018). The absorptive capacity of technology requires high-frequency interpersonal communication between scientists, engineers, and the enterprise's R&D personnel (Carayannis et al., 2000). Therefore, it is reasonable to suppose that an industrial enterprise's absorptive capacity in a region is like a threshold that moderates the effect of U-I knowledge creation on regional low carbon innovation performance (Aboelmaged and Hashem, 2019).

Likewise, we argue that the existing absorptive capacity of industrial enterprises will influence the extent to which acquiring knowledge from universities and commercializing it to low carbon innovation performance takes place (Hou et al., 2019). Industrial enterprises may not only acquire valuable strategic assets through U-I knowledge commercialization activities but also subsequently adapt and exploit those assets to benefit their home region's low carbon innovation development (Caloghirou et al., 2021). According to Yi et al. (2021), embedded tacit knowledge from U-I knowledge commercialization is not immediately available for industrial enterprises, and regional low carbon innovative performance is unlikely to benefit from U-I knowledge acquisition without a certain scientific base and amount of R&D experience. Thus, a higher degree of an industrial enterprise's absorptive capacity is likely to be associated with better low carbon innovation performance in the home region (Aboelmaged and Hashem, 2019; Zhang et al., 2020). Our study, therefore, hypothesizes:

H3a: The industrial enterprise's absorptive capacity has a positive impact on regional low carbon innovation performance.

H3b: The industrial enterprise's absorptive capacity has a positive moderation impact on the relationship between U-I knowledge creation and regional low carbon innovation performance.

H3c: The industrial enterprise's absorptive capacity has a positive moderation impact on the relationship between U-I knowledge commercialization and regional low carbon innovation performance.

2.4 Digitization level and regional low carbon innovation performance

Previous studies have suggested that the development of digitization in a region can have a positive impact on RIS and KM (Nguyen and Burgess, 2014; Maravilhas and Martins, 2019). Hultman et al. (2012), Arenal et al. (2020), and Elia et al. (2020) found that regional intelligence is a strong driver of regional low carbon innovation, with digital equipment being the main tool for gaining and disseminating intelligence. Similarly, Zhou et al. (2020) and Yang et al. (2022) asserted that the policy of developing digitization to improve low carbon innovation can stimulate the efficiency of KM and technical exchange among different organizations. Therefore, we argue that the moderating effect of regional digitization level on U-I knowledge creation and commercialization should be explored (Arenal et al., 2020; Zhou et al., 2020; Yang et al., 2022).

When considering the moderation effect of regional digitization level on the relationship between U-I knowledge creation and regional low carbon innovation, we expect the positive effect to dominate. Universities and industrial enterprises located in highly digitized regions may have faster access to knowledge and save time for communicating with R&D partnerships, which can lead to more sufficient resources and time for conducting low carbon innovation activity (Elia et al., 2020). Moreover, the development of digitization in a region is an effective tool for improving external communications, providing services for universities and industrial enterprises with faster response times and information access (Higón, 2012). Therefore, a higher degree of digitization level in a region can accelerate the impact of U-I knowledge creation on regional low carbon innovation performance.

Regarding the impact of U-I knowledge commercialization on regional low carbon innovation performance, we argue that the level of digitization in a region will influence this relationship. Acquiring knowledge from universities is a vital activity for effective knowledge commercialization, and a sufficient and robust digital infrastructure can provide easier access to advanced knowledge or information, facilitating R&D activities (Maravilhas and Martins, 2019). Industrial enterprises may pursue low carbon innovation if they believe that they will be able to access appropriate knowledge to differentiate their products and profit from their commercialization efforts (Bjerregaard, 2010). Therefore, we hypothesize that regional digitization level is necessary to fully realize the benefits of knowledge transfer for regional low carbon innovation performance, and we propose the following hypotheses:

H4a: The regional digitization level has a positive impact on regional low carbon innovation performance.

H4b: The regional digitization level has a positive moderation impact on the relationship between U-I knowledge creation and regional low carbon innovation performance.

H4c: The regional digitization level has a positive moderation impact on the relationship between U-I knowledge commercialization and regional low carbon innovation performance.

3. Research sample and methods

3.1 Empirical setting and data

This study constructed a balanced panel data for 31 provinces and municipalities for the period of 2008-2019 to test our framework and hypotheses. Information regarding China's low carbon innovation performance was obtained from the Chinese Innovation Research Database (CIRD), from which our study extracted low carbon patent information, such as patent application and granted. Because this study focuses on the effects of U-I knowledge creation and U-I knowledge commercialisation on innovation performance, we also collected information regarding university knowledge transfer, U-I knowledge creation, U-I knowledge commercialisation and industry absorptive capacity from China Higher education compendium statistics, China statistics yearbook and China statistics yearbook on science and technology. This study further collected information on regional digitalization from the China information almanac. Due to the

limitation of the information availability, this study limited the industry empirical context to above the designated size that has been identified in prior studies. After removing noncompliance information, we used a unique province ID code to link the information from the above sources for each province. We merged the data from the four sources and arrived at 4832 pieces of data with 372 observations for the 12 years.

3.2 Measures

Dependent variable

Previous studies have considered several different indicators to measure the regional low carbon innovation performance, some of them may effectively capture the quantity aspect of low carbon innovation, such as the number of low carbon patents or new low carbon product sales (Albort-Morant et al., 2018, Du et al., 2019). Typical low carbon innovation outputs are measured by technology development inform of the patent. Not all innovations are patented, but the process of patent generation ensures that strict accordance with the regulations and the patent documents typically provide useful technological and organizational information (Malerba et al., 1997). On the other side, the patent provides a more accurate indication of innovation performance than alternative measures such as new products (Acs et al., 2002). New products are often loosely defined and can be potentially over-recorded by firms in order to gain subsidies in many countries (Li et al., 2016). Therefore, patent grants are the favoured measure used in most previous studies (Choi et al., 2011; Hong and Su 2013). In this study, the dependent variable is regional low carbon innovation performance (*INN*) as measured by the natural log of the low carbon patent grants per 10000 inhabitants made each year (Wang et al., 2020; Zhao et al., 2021).

Independent variable

In this study, we explore four independent variables that are associated with regional low-carbon innovation performance. Our first independent variable is U-I knowledge creation, defined as the score of external expenditure on R&D in industrial enterprises to domestic universities and external expenditure on R&D in universities to domestic industrial enterprises. Previous studies have generally included R&D input, R&D output, and R&D efficiency as indicators of U-I knowledge creation (Barnes et al., 2002; Becker and Dietz, 2004; Shi et al., 2020). However, U-I knowledge creation in a region involves a series of activities, such as R&D cooperation between universities and

industrial enterprises and R&D expenditure of both parties (Scandura, 2016; Bellini et al., 2019). Therefore, we argue that the best indicator of U-I knowledge creation in a region is a composite score composed of R&D expenditure of universities and industrial enterprises. In this way, U-I knowledge creation can be measured as one proxy variable that is more consistent with the understanding of U-I knowledge creation in this study.

The second independent variable is the U-I knowledge commercialisation. Indicators of knowledge commercialisation in previous studies have mainly included product sale volume, the productivity level of enterprises, and firms' profit (Kergroach et al., 2018). However, those indicators may not be applicable in the context of U-I collaboration because U-I knowledge commercialisation involves a series of knowledge transfer activities, such as transferring knowledge from the university, fixing a price for knowledge, and return for knowledge commercialising by industrial enterprises (Fu et al., 2008). Therefore, the best indicator of U-I knowledge commercialisation in this study is a composite score including the number of contracts of technology transfers from universities to industrial enterprises, the value of technology transfers from universities to industrial enterprises, and the real income of industrial enterprises (Robertson et al., 2019; Shi et al., 2020). By creating these index groups, our study converts the single indicator into a comprehensive variable to make it more associated with regional low-carbon innovation performance (Zhang et al., 2020; Zhou et al., 2020).

Our third independent variable in this study is the absorptive capacity of industrial enterprises. Existing research has used human resources, such as the full-time equivalent of R&D personnel or education level per capita, as indicators of absorptive capacity (Li et al., 2016). However, in the context of U-I collaboration, the absorptive capacity of industrial enterprises cannot be appropriately proxied by these because of its multidimensional construct. Moreover, it is not feasible to calculate absorption capacity separately only from human resources at the regional level (Fu, 2008). Therefore, the absorptive capacity of industrial enterprises in a region should take into account various dimensions, including R&D institutions, the full-time equivalent of R&D personnel, R&D expenditure, R&D project, and R&D project expenditure of industrial enterprises (Lin et al., 2011; Albort-Morant et al., 2018). Thus, we use a

composite score of the above index as the indicator of the absorptive capacity of industrial enterprises in a region.

The fourth and final independent variable in our study is the level of regional digitization. To measure this variable, we use a composite score of multiple indicators that reflect the state of digital infrastructure and connectivity in a given region (Liu et al., 2011; Wang et al., 2021). These specific indicators include the number of landline and mobile telephone subscribers per 10,000 people, the number of broadband ports providing Internet access, and Internet penetration. These indicators have been found to be strongly associated with regional digitization levels (Wang et al., 2021). While previous studies have used fixed and mobile telephone subscriptions to represent ICT infrastructure indicators and Internet users as a proxy for digitization level (Ollo and Aramendía, 2012; Nguyen and Burgess, 2014), Hamad (2018) constructed a composite index of digitization development that includes landline telephones, mobile phones, and Internet penetration to analyze the impact of digitization on economic development.

Control Variable

This study has five control variables. First, GDP was measured using the logarithmic transformation of the regional GDP growth rate (Ouyang and Fu, 2012). Second, regional fixed investment efficiency was included, which was measured by the ratio of fixed investment to regional GDP. GDP and fixed investment efficiency might influence the results since regions with higher GDP tend to produce more low carbon innovation performance than those with lower GDP, and fixed investment efficiency is associated with the level of digitalization in the region (Jiang et al., 2011). Information on GDP and fixed investment efficiency was obtained from the China statistics yearbook. Third, research intensity was measured as the ratio of R&D expenditure over the GDP (Fu, 2008), since the higher the degree of research intensity, the more likely industrial enterprises and universities will have more R&D interaction (Fu, 2008; Li et al., 2016). Research intensity data was collected from the China Statistical Yearbook on Science and Technology. Fourth, high education level was measured as the percentage of the population entering higher education in the region (Boccanfuso et al., 2015), as the high education level might be an important factor of industrial enterprises' absorptive capacity and knowledge generation in university (Flor et al., 2018; Zhang et al., 2020). Table 1 shows the detailed definitions of each variable.

Table 1 Description of Variables

Variable name	Acronym	Operationalization
Regional Low Carbon Innovation Performance	$INN_{i,t}$	Natural log of low carbon technology patents scores of region i in year t .
Regional U-I Knowledge Creation	$KNA_{i,t}$	Natural log of U-I knowledge creation scores of region i in year t .
Regional U-I Knowledge Commercialization	$KNC_{i,t}$	Natural log of U-I knowledge commercialization in region i in year t .
Regional Absorptive Capacity of Industrial Enterprises	$ABS_{i,t}$	Natural log of industrial enterprises absorptive capacity score of region i in year t .
Regional Digitalization Level	$DIG_{i,t}$	Natural log of digitalization score of region i in year t .
GDP	$GDP_{i,t}$	Natural log of GDP growth rate of region i in year t .
Research Intensity	$RDI_{i,t}$	Natural log of R&D expenditure /GDP (percent) of region i in year t .
Technical Markets	$TEC_{i,t}$	Natural log of technology market transaction volume of region i in year t .
High Education Level	$EDU_{i,t}$	Natural log of the percentage of the population entering higher education of region i in year t .
Fixed Investment Efficiency	$INV_{i,t}$	Natural log of fixed investment /GDP (percent) of region i in year t .

3.3 Model Specification

This study follows the approach of many previous studies on regional low carbon innovation performance and builds its model on the Knowledge Production Function (KPF), which was initially developed by Griliches in 1979. Since then, the KPF has been successfully applied to a series of empirical studies at both the national and regional levels. The KPF is similar in structure to a standard production function, where the output is the regional low carbon innovation performance in region i at time t . This model assumes that innovation, the result of successful R&D inputs, is a function of the inputs to the R&D process (Cohen and Levinthal, 1989).

$$INN_{i,t} = a \times (RDI_{i,t})^a \quad (1)$$

Where

$INN_{i,t}$ = Low carbon innovation performance of region i in year t .

$RDI_{i,t}$ = R&D inputs of region i in year t .

According to Griliches (1998), the generation of new knowledge depends on two factors: the innovatory effort made and the characteristics of the region. To keep the knowledge production function simple, this study accounts for the main extension-research inputs. We adopt the general specification proposed by Fritsch (2002), which includes our hypothesised variables (U-I knowledge creation, U-I knowledge

commercialisation, industry absorptive capacity, and regional digitalization) as well as control variables (GDP, research intensity, technical markets, high education, and fixed investment efficiency). The basic structure of the knowledge production function assumes that innovation, which is the outcome of successful R&D inputs, is a function of these inputs (Cohen and Levinthal, 1989).

$$INN_{i,t} = A + (KNA)_{i,t}^{\alpha} \times (KNC)_{i,t}^{\beta} \times (ABS)_{i,t}^{\gamma} \times (DIG)_{i,t}^{\delta} \times Z_{i,t}^{\theta} \quad (2)$$

Where

$KNA_{i,t}$ = U-I knowledge creation score of region i in year t .

$KNC_{i,t}$ = U-I knowledge commercialisation in region i in year t .

$ABS_{i,t}$ = Absorptive capacity of industrial enterprises score of region i in year t .

$DIG_{i,t}$ = Regional digitalization level score of region i in year t .

$Z_{i,t}$ = Vector of control variables of domestic region i in period t

$A, \alpha, \beta, \gamma, \delta, \varepsilon, \theta$ are parameters to be estimated.

This study takes logarithms of both sides of equation (2) and thus the regression model to be estimated takes the form:

$$\log(INN_{i,t}) = a + \alpha \times \log(KNA_{i,t}) + \beta \times \log(KNC_{i,t}) + \gamma \times \log(ABS_{i,t}) + \delta \times \log(DIG_{i,t}) + \varepsilon \times \log(Z_{i,t}) + \mu_{i,t} \quad (3)$$

Where

$a = \log(A)$ and $\mu_{i,t}$ are dummy variables (years).

Given the logarithms formulation of the regression model, the estimated coefficients may be interpreted as elasticities. This study will also incorporate additional variables in the model to capture the interaction effects between the hypothesised variables.

3.4 Estimation method

Our dependent variable is regional low carbon innovation performance. Previous research has suggested that reverse causation can generate estimation problems in studies of innovation performance. This means that the independent variables may impact regional low carbon innovation performance, but innovation may also have an

impact on some independent variables (Li et al., 2016; Wang et al., 2020). Under these circumstances, U-I knowledge creation and U-I knowledge commercialisation may lead to better regional low carbon innovation performance, but more innovative industrial enterprises are also likely to cooperate with universities. These endogeneity issues may arise through industry enterprises' learning effects or through the transfer of better knowledge performing universities. Ordinary Least Squares (OLS) and within estimators tend to overestimate the effects of the explanatory variables and are unable to address the simultaneity and endogeneity issues (Liu et al., 2014). Furthermore, it is necessary to include a lagged dependent variable as a further control. Our study lagged all the explanatory variables by one year to account for the fact that some predicted effects take time to materialize (Li et al., 2016). The use of a lag structure allowed us to control for possible simultaneity bias (Aitken and Harrison, 1999).

Many studies have suggested that selecting the appropriate instrumental variables in general economic statistics research is difficult, and the Generalized Method of Moments (GMM) exhibits many advantages (Arellano and Bond, 1991; Blundell and Bond, 2000; Wang et al., 2020). In particular, GMM can use a lagged dependent variable as an instrumental variable to further control estimation. Hence, this study uses the panel data GMM estimation method to conduct the analysis. This method is regarded as a reasonable method for dealing with unobserved heterogeneity, endogeneity, and situations where the explanatory variables are not strictly exogenous (Blundell and Bond, 2000; Liu et al., 2014). Meanwhile, GMM is also suitable for dynamic panel data because it allows the use of first differences as instruments and exploits the available moment conditions in the sample more fully (Blundell and Bond, 2000). To this end, this study uses the difference of the lagged dependent and explanatory variables as instruments and Hansen's test to check their overall validity. Meanwhile, the Arellano-Bond test for AR is also used to detect the existence of first or second-order serial correlation.

4. Results

4.1 Main results

Table 2 reports the descriptive statistics and pairwise correlations of the variables used. All correlations are fairly low, which is expected. We calculated variance inflation factors (VIFs) and found that all VIFs were substantially below the acceptable level of

10 (Neter et al., 1985). The results thus indicate that multicollinearity is not a serious concern. To further eliminate the problem of multicollinearity and enhance the interpretation of interactions, this study centred the variables before generating those interaction terms (Aiken and West, 1991).

Table 2 Correlation matrix

	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>INN</i>	<i>COL</i>	<i>KNO</i>	<i>ABS</i>	<i>DIG</i>	<i>GDP</i>	<i>RDI</i>	<i>TEC</i>	<i>EDU</i>	<i>INV</i>	<i>VIF</i>
<i>INN</i>	369	5.560	1.696	1	0.82*	0.70	0.72*	0.69**	-0.49	0.84*	0.25	0.56	0.03	
<i>KNA</i>	372	0.118	0.153	0.64	1	0.78	0.80	0.72	-0.26	0.85*	0.03*	0.38	-0.23	3.14
<i>KNC</i>	372	-3.615	3.141	0.73	0.50*	1	0.77	0.63	-0.03	0.76	-0.04	0.27	-0.38	2.63
<i>ABS</i>	372	0.200	0.252	0.56	0.50	0.47*	1	0.74	0.00	0.76	-0.20*	0.18*	-0.36	3.65
<i>DIG</i>	372	0.302	0.160	0.63*	0.56	0.54	0.77	1	-0.20*	0.63	-0.05	0.33	-0.31*	3.29
<i>GDP</i>	371	2.221	0.323	-0.43	-0.21	-0.02	-0.03	-0.15	1	-0.27	-0.46	-0.59	-0.61	3.77
<i>RDI</i>	372	0.235	0.661	0.82	0.70*	0.70**	0.50	0.57	-0.25	1	0.26**	0.59	-0.19	4.86
<i>TEC</i>	372	0.013	0.012	0.22	0.48	-0.05	-0.13	0.06	-0.35	0.32	1	0.63	0.29	2.93
<i>EDU</i>	372	0.123	0.072	0.52	0.64	0.27*	0.06*	0.29*	-0.43	0.67	0.73	1	0.18	5.74
<i>INV</i>	372	8.912	4.873	0.02	-0.22	-0.31	-0.28	-0.30	-0.68	-0.18	0.16	-0.02	1	3.60

Note: Data collected from various official statistical yearbooks and bulletins; China industry statistics yearbook; The China Statistical Yearbook on Science and Technology; The China Statistical Yearbook.

Table 3 reports our GMM regression result. One concern that may arise is that the U-I knowledge creation and U-I knowledge commercialisation variable may be endogenous, as innovation performance may also influence those U-I collaboration activities. However, this possibility is likely to be minimal because the collaboration between industrial enterprises and universities in China has been widely carried out around the country in recent years, which leads the collaboration to be less likely to be limited on certain firm (or university) specific characteristics (Zhou and Tang, 2020). Nevertheless, our study took measures to overcome this concern by incorporating a wide set of individual-level covariates as controls for important differences in firm characteristics. Furthermore, we adoption of a lag structure for independent variables should also help to control for possible endogeneity (Aitken and Harrison, 1999). Furthermore, the consistency of the GMM estimators requires valid instruments and also the absence of second-order serial correlation (Blundell and Bond, 2000). Our study using the lagged dependent and explanatory variables from years 1-3 as instruments and also employ the Hansen test for over-identifying restriction and overall validity of the instruments in the estimation process. The insignificant values of the Hansen J-statistics in Model (1)-(6) support the view that the instrumental variables are uncorrelated to residuals. Moreover,

the Arellano–Bond tests in all models indicate that the second-order serial correction tests AR (2) and Hansen tests are insignificant that provide the suitability of GMM conditions. Model (1) serves as the baseline model and includes control variables only. The main independent variables, U-I knowledge creation, U-I knowledge commercialisation, absorptive capacity of industrial enterprises and regional digitalization level, is added to Model (2)-(6). Hence, this section focusses the discussion on models (2)-(6).

Table 3 GMM regression results

Variable	(1)	(2)	(3)	(4)	(5)	(6)
<i>INN</i>	0.069*** (8.34)	0.478*** (5.57)	0.191*** (5.88)	0.112*** (6.01)	0.109*** (5.36)	0.093*** (7.27)
<i>GDP</i>	0.056 (8.23)	0.137*** (8.12)	0.126*** (8.03)	0.142*** (5.44)	0.123*** (6.91)	0.184*** (3.18)
<i>RDI</i>	0.122 (2.87)	0.230* (1.63)	0.331* (2.21)	0.261** (1.67)	0.245 (0.91)	0.367 (-0.27)
<i>TEC</i>	11.224 (0.33)	9.512 (1.12)	8.403* (1.68)	12.364 (1.53)	11.221 (1.60)	12.517 (0.31)
<i>EDU</i>	1.326 (0.36)	1.852** (2.37)	1.612** (2.21)	1.832 (1.22)	1.995 (1.18)	1.787 (1.37)
<i>INV</i>	0.007 (1.22)	0.026** (3.93)	0.031 (2.61)	0.056 (1.98)	0.020*** (3.58)	0.016** (2.42)
<i>KNA</i>		1.454*** (2.89)	1.698*** (2.23)	2.301*** (1.86)	0.460** (2.36)	1.929 (1.23)
<i>KNC</i>		0.142*** (1.96)	0.116** (1.73)	0.263** (1.12)	0.109** (0.82)	0.125* (1.33)
<i>ABS</i>		0.979*** (2.81)	0.612** (2.32)	0.727* (2.66)	0.413* (1.86)	0.681 (0.70)
<i>DIG</i>		1.469*** (2.55)	0.826*** (1.85)	0.636** (1.63)	0.568*** (3.42)	0.923* (1.76)
<i>KNA×ABS</i>			0.023 (1.06)			
<i>KNC×ABS</i>				1.722*** (2.35)		
<i>KNA×DIG</i>					1.061** (2.13)	

<i>KNC</i> × <i>DIG</i>						0.237*** (3.60)
<i>AR</i> (1)	0.323	0.088	0.117	0.268	0.143	0.016
<i>AR</i> (2)	0.112	0.454	0.522	0.653	0.669	0.484
<i>Hansen J Statistics</i>	0.311	0.189	0.369	0.237	0.481	0.165
<i>Observations</i>	372	372	372	372	372	372
<i>Number of regions</i>	31	31	31	31	31	31

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In model (2), the lagged value of the dependent variable – regional low carbon innovation performance ($INN_{i,t}$) is significant as expected, so as variables of U-I knowledge creation ($KNA_{i,t}$) and U-I knowledge commercialisation ($KNC_{i,t}$). This result suggests that regional low carbon innovation performance improvement is a gradual and accumulated process. In this sense, during the formulation of low carbon innovation principles and U-I collaboration policies, the government should consider the dynamic development process of the U-I knowledge creation, U-I knowledge commercialisation and low carbon innovation capacities in different regions, as well as the long-term development of regional low carbon innovation performance and those U-I collaboration activities.

Furthermore, all four hypothesised variables and their direct effects on innovation performance are highly significant in model (2). In particular, the U-I knowledge creation ($KNA_{i,t}$) has a strong effect ($p < 0.01$), where the estimated coefficient is 1.454, hypothesis H1 is thus supported. Therefore, it is reasonable to argue that through the U-I knowledge creation, the universities and industrial enterprises contribute to the development of low carbon innovation performance, while the universities and industrial enterprises work together in China's RIS. Meanwhile, U-I knowledge creation as the university and industrial enterprises interaction mechanism not only facilitate the transformation of scientific and technological achievements but also knowledge exchange between the university and industrial enterprises in the innovation ecosystem. The coefficient of the U-I knowledge commercialisation ($KNC_{i,t}$, 0.142, $p < 0.05$) is positive and significant in this model, thus providing support for hypothesis H2, which predicts that the knowledge acquisition from university is positively associated with the regional low carbon innovation performance in China. The coefficient of both U-I knowledge creation and U-I knowledge commercialisation appeared to justify our

previous view that the U-I knowledge creation is more effort for driving regional innovation performance development. Meanwhile, the coefficient of the absorptive capacity of industrial enterprises ($ABS_{i,t}$, 0.979, $p<0.01$) is positive and significant in model (2) suggesting that a professional workforce and R&D investment is a necessary prerequisite for good innovation performance, supporting hypothesis H3a. The last predictor variable in Model 2 is the regional digitalization level ($DIG_{i,t}$) in China. The coefficient of this variable is positive and significant in this model, thus providing support for hypothesis H4a. The coefficient of this variable indicates that 1% increase in digitalization development will lead to a 1.469% increase in the low carbon patent grants.

In models (3) – (6), this study also considered the four interaction terms. In model (3), the coefficient of the interaction between U-I knowledge creation ($KNA_{i,t}$) and absorptive capacity of industrial enterprises ($ABS_{i,t}$) of industrial enterprises is positive but statistically insignificant, perhaps because the expected positive and negative effects have cancelled each other out. Therefore, the hypothesis H3b, the moderation role of the absorptive capacity on the relationship between U-I knowledge creation ($KNA_{i,t}$) and regional low carbon innovation performance ($INN_{i,t}$) is not supported. In model (4) the coefficient of the interaction term between U-I knowledge commercialisation ($KNC_{i,t}$) and absorptive capacity of industrial enterprises ($ABS_{i,t}$) of industrial enterprises is positive and significant at 1% level. Thus, the hypothesis H3c, the moderating effect of the absorptive capacity on the relationship between U-I knowledge commercialisation and regional low carbon innovation performance is confirmed. Our result seems to confirm that the absorptive capacity of industrial enterprises is not always important for U-I collaboration activities, especially when the industrial enterprises launched knowledge creation project with universities.

In model (5), the coefficient of the interaction term between U-I knowledge creation ($KNA_{i,t}$) and regional digitalization level ($DIG_{i,t}$) is positive and significant at 5% level. It thus appears that the effects on regional low carbon innovation performance of U-I knowledge creation ($KNA_{i,t}$) and regional digitalization level ($DIG_{i,t}$) are additive. Thus, the hypothesised H4b, the moderating effect of regional digitalization level ($DIG_{i,t}$) on the relationship between U-I knowledge creation ($KNA_{i,t}$) and regional low

carbon innovation performance ($INN_{i,t}$) is confirmed. In model (6), the coefficient of the interaction term between U-I knowledge commercialisation ($KNC_{i,t}$) and regional digitalization level ($DIG_{i,t}$) is positive and significant at 1% level. Therefore, hypothesis H4c that regional digitalization level positively moderates the relationship between U-I knowledge commercialisation ($KNC_{i,t}$) and regional low carbon innovation is supported. Our empirical results clearly show that the positive impact of U-I knowledge commercialisation ($KNC_{i,t}$) on regional low carbon innovation performance is enhanced in regions where digitalization have a greater level.

4.2 Robustness checks

The above empirical analysis has proven that U-I knowledge creation and U-I knowledge commercialisation can increase regional low carbon innovation performance. In this section, our study conducted robustness checks to confirm the consistency of the above results. We chose the one-step system GMM to estimate the models because it could efficiently manage endogeneity problems of a panel model. In this section, our study employed 2SLS as an alternative estimation method with 31 provinces over the period of 2008-2019 to test the robustness of our main findings.

To test the influence of U-I knowledge creation and U-I knowledge commercialisation on regional low carbon innovation performance using 2SLS regression, we have to identify a valid instrumental variable. Following standard practice (Gujarati, 2012), one instrumental variable that was used is the R&D investment intensity. A valid instrument should be correlated with the suspected endogenous variable (U-I knowledge creation and U-I knowledge commercialisation) while simultaneously being orthogonal to the error term. When a Chinese region has a higher R&D investment intensity, it has a larger demand for knowledge from universities. Moreover, R&D investment has been a crucial source of advanced knowledge for many emerging economies seeking to improve their low carbon innovation capabilities. Thus, our study posits that R&D investment intensity is an appropriate instrumental variable.

Following the result of 2SLS in Table 4, the estimation also confirms the strength of our model. Durbin score and Wu-Hausman tests are used to determine the endogeneity, with the null hypothesis that all the variables are exogenous, so our model has a

significant score that rejects the null hypothesis and accepts the alternative hypothesis of endogeneity. The minimum eigenvalue or F - statistics of the first stage regression are much greater than the critical value and statistically significant at the 1% level. Thus, the null hypothesis of weak instruments is rejected. Adding to model 2, U-I knowledge creation and U-I knowledge commercialisation could increase regional low carbon innovation performance, while digitization can help to facilitate the low carbon innovation performance development in the case of the regional perspective. Furthermore, the coefficient of R&D investment intensity ($RDI_{i,t}$) is positive also expresses the principal role of R&D in the concept of RIS theory. It is noted that 1% increase in R&D investment to a 7.62% increase in regional low carbon innovation performance. In short, these empirical results unravel the interactive relationship between regional low carbon innovation performance. Our robustness test has confirmed the consistency of the above empirical results, the results of 2SLS conform to our primary findings and indicate the reliability of our findings for theoretical and practical implications.

Table 4 Robustness checks

Variable	GMM Full Sample	2SLS
<i>INN</i>	0.478*** (5.57)	0.728*** (20.14)
<i>GDP</i>	0.137*** (8.12)	-1.139*** (-5.33)
<i>RDI</i>	0.230* (1.63)	0.762*** (4.79)
<i>TEC</i>	9.512 (1.12)	4.598 (0.93)
<i>EDU</i>	1.852** (2.37)	-1.241 (-1.03)
<i>INV</i>	0.026** (3.93)	0.018 (1.02)
<i>KNA</i>	1.454*** (2.89)	0.376*** (2.82)
<i>KNC</i>	0.142*** (1.96)	0.062*** (6.19)
<i>ABS</i>	0.979*** (2.81)	0.190*** (2.95)

<i>DIG</i>	1.469*** (2.55)	0.353*** (3.14)
<i>Observations</i>	372	372
<i>R--squared</i>		0.850
<i>Number of regions</i>	31	31
<i>Durbin Score (Tests of endogeneity)</i>	\	4.594**
<i>Wu–Hausman</i>	\	4.536**
<i>Min. eigenvalue (First-stage regression summary statistics)</i>	\	24.761***
<i>AR(1)</i>	0.085	\
<i>AR(2)</i>	0.475	\
<i>Sargan Statistics</i>	0.846	\
<i>Hansen J Statistics</i>	0.189	\

*t statistics in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01*

5. Discussion and conclusion

This study has examined the impact of U-I knowledge creation and U-I knowledge commercialisation on regional low carbon innovation performance. We used a novel and unique panel dataset made up of data on regional low carbon innovation performance combined with U-I knowledge creation and U-I knowledge commercialisation obtained from several statistics yearbooks. We employed the entropy method to deal with each dependent and independent variable score that is as realistic as possible to control the credibility and accuracy, and we estimated the impact of U-I knowledge creation and U-I knowledge commercialisation by GMM regression on the matched sample. We hypothesized that U-I knowledge creation and U-I knowledge commercialisation have a positive effect on the regional low carbon innovation performance. Meanwhile, we also identified two moderating factors -- the regional absorptive capacity of industrial enterprises and the regional digitization level. Our study integrated low carbon innovation into the RIS model, revealing the influence mechanism of U-I collaboration on the regional low carbon innovation performance. The results further revealed that the regional digitization level is a critical moderation factor that facilitates the regional low carbon innovation performance, but the absorptive capacity is not always important in U-I collaboration activities.

The introduction of low-carbon innovation into the RIS theory and the development of the RLCIS concept are important contributions of this study to the existing literature. The results provide a framework for the integration of low-carbon innovation into regional innovation systems, highlighting the need for U-I knowledge creation and

commercialization to promote sustainable development. The findings are particularly relevant in the context of the current global climate crisis, where a transition to low-carbon technologies is essential to mitigate the negative impact of climate change. Moreover, the study challenges the conventional view that absorptive capacity is a key factor in determining the success of RIS and KM initiatives. While the role of absorptive capacity has been emphasized in many prior studies, our findings suggest that other factors such as U-I collaboration, knowledge creation, and commercialization are equally important for promoting low-carbon innovation. These results imply that policy interventions should focus on fostering U-I collaboration, knowledge creation, and commercialization, and other related factors, rather than solely on enhancing absorptive capacity.

5.1 Implications for theory

Our research contributes to the advancement of RIS theory by proposing an integrated framework that incorporates the concept of low-carbon innovation. Building on the RIS theory, we further suggest the concept of RLCIS to capture the unique features and complexities of the low-carbon innovation process in regional contexts. As an emerging research area, only a few studies (e.g., Yin et al., 2019) have mentioned the concept of RLCIS, and our study aims to provide more empirical evidence for RLCIS and promote its development. The RIS theory has been widely used to analyze the innovation process in regional contexts, highlighting the importance of the interaction between different actors, including universities, research institutions, firms, and governments. However, the conventional RIS theory mainly focuses on the quantity or economic performance of innovation (Cooke, 1992; Nelson, 1993; Freeman, 1995; Asheim et al., 2011; Li et al., 2016; Wang et al., 2020), but gives less consideration to the specific features and complexities of low-carbon innovation, which involves the development and diffusion of innovative technologies, products, and patents that reduce greenhouse gas emissions and enhance sustainability (Kivimaa and Kern, 2016; Zhang and Li, 2019). By incorporating the concept of low-carbon innovation, our integrated framework offers a more comprehensive and nuanced understanding of the low-carbon innovation performance development mechanism, which is critical for promoting sustainable development.

Our study focuses on a large emerging economy where promoting low-carbon innovation, developing cooperation between universities and industrial enterprises, and enhancing sustainable development capabilities are government priorities (Liu et al., 2011). Drawing upon previous innovation studies (e.g., Bettiol et al., 2013; Li et al., 2016; Aboelmaged and Hashem, 2019; Wang et al., 2020; Zhao et al., 2021), our integrated framework captures the driving forces of regional low-carbon innovation performance from the perspective of U-I knowledge creation and U-I knowledge commercialization. In short, our research extends the RIS theory by proposing the concept of RLCIS and providing an integrated framework that considers low-carbon innovation performance in the context of U-I collaboration. By highlighting the unique features and complexities of low-carbon innovation, our study contributes to the development of RIS theory and offers insights for policymakers and practitioners to promote sustainable development in regional contexts.

Second, we challenge the dominant view about the importance of industrial enterprises' absorptive capacity in RIS and KM theories. The moderation role of the absorptive capacity of industrial enterprises in a region on the relationship between U-I knowledge creation and regional low carbon innovation performance is not universal. The result suggests that U-I knowledge creation are not required industrial enterprises have the well-established absorptive capacity, less-experienced industrial enterprises are able to reduce the reliance on the absorptive capacity needed for creating low carbon innovation performance. This finding addresses an important gap in the existing literature where empirical evidence on the relationship between U-I knowledge creation, U-I knowledge commercialisation, the absorptive capacity of industrial enterprises and regional low carbon innovation performance is limited (Li, 2011; Flor et al., 2018 Aboelmaged and Hashem, 2019). Furthermore, this finding offers valuable empirical evidence on what determines the intensity of U-I knowledge creation and U-I knowledge commercialisation in the first place. The result also extends existing studies (e.g., Chalmers and Balan-Vnuk, 2013, Zhang et al., 2020; Zhou and Tang, 2020) by examining the differential moderation impact of industrial enterprises' absorptive capacity on U-I knowledge creation and U-I knowledge commercialisation in the context of a large emerging economy.

Third, this study extends our understanding of U-I collaboration activities and regional low carbon innovation performance. Differing from previous research that has only examined the impacts of U-I collaboration internal factors on the innovation development, our study considers the external factor -- the regional digitization level. we have further investigated the interaction between regional digitization level and regional low carbon innovation performance, and whether the interaction between regional digitization level and U-I collaboration activities affects the regional low carbon innovation performance. The results from our research help to identify the condition under which digitization level is more salient in shaping low carbon innovation performance, a relationship which has been underexplored in existing studies (Nguyen and Burgess, 2014; Hamad, 2018, Ollo-López and Aramendía-Muneta, 2012). The findings enhance our understanding of the importance of regional digitization development in the form of low carbon innovation performance. regional digitization level is also an important contingency factor that positively moderates the impact of both U-I knowledge creation and U-I knowledge commercialisation on the low carbon innovation performance. Therefore, our research broadens the impact of regional digitization development and provides a more complete account of low carbon innovation performance development in an emerging economy.

Finally, for the U-I collaboration and regional innovation literature, our study provides new insights into the previous contradictory assertions (Shi et al., 2020; Østergaard and Drejer, 2022) in the literature on the relationship between U-I collaboration and innovation, by providing theoretical arguments and empirical evidence. Different from the previous study that concentrates more on motivation, institution, and organisation heterogeneity of U-I collaboration (Perkmann et al., 2013; Di Maria et al., 2019), our study's unique focus on the different types of U-I collaboration activities, highlight the discrepant impact of both U-I knowledge creation and U-I knowledge commercialisation on regional low carbon innovation performance. Differentiating U-I knowledge creation and U-I knowledge commercialisation also enables us to evoke a new argument that improves the existing conclusions in the U-I collaboration and regional innovation literature. Our empirical result suggests that the contribution of U-I knowledge creation is greater than U-I knowledge commercialisation in low carbon innovation performance development. This explained in a certain extent the reasons why some U-I collaborations cannot bring adequate low carbon innovation

performance. Meanwhile, our findings of the discrepant effect of both U-I knowledge creation and U-I knowledge commercialisation provide both theoretical and empirical support for the argument that at high-stress levels of sustainable development, the university and industrial enterprise should conduct more knowledge creation, which could bring more low carbon innovation performance. Therefore, we fill the gap in the extant literature on U-I collaboration and low carbon innovation by offering a perspective of different collaboration types and calling for more research on this contradictory phenomenon.

5.2 Implications for practice

This study also offers practical implications for policymakers and industrial enterprise managers. Our results suggest that a favorable policy environment for U-I collaboration enhances regional low carbon innovation performance through U-I knowledge creation and U-I knowledge commercialization. This proves to be an effective way of developing low carbon innovation as it improves the ability of industrial enterprises to innovate in this area and motivates universities to participate actively in low carbon innovation. Government policies on U-I collaboration should focus on funding support for the basic needs of industrial enterprises in low carbon innovation and their survival and development. Furthermore, our analysis suggests that regional digitization levels are critical to achieving low carbon innovation objectives. Thus, increasing regional digitization levels and accelerating knowledge transfer or sharing will not only bring more advanced knowledge directly to industrial enterprises, but may also facilitate low carbon innovation performance in a region.

For managers of industrial enterprises, when collaboration with the university is motivated by low carbon innovation activities, absorptive capacity is not always necessary to achieve this objective. Industrial enterprises can reduce their dependence on their internal absorptive capacity through knowledge creation activities with universities. Although this might pose intense competitive pressures, to which they have never been exposed, it can also provide opportunities for emerging economies to accelerate regional low carbon innovation performance and catch up with global low carbon innovation leaders in a relatively short period of time. Instead, industrial enterprises can achieve better low carbon innovation performance and simultaneously leverage their own distinctive ownership advantages through knowledge

commercialization projects to exploit acquired intangible strategic assets (such as technologies, IP, etc.) when they have appropriate absorptive capacity.

5.3 Limitations and directions for future research

This paper is not without limitations. As with similar single economy studies, one limitation of this study concerns the generalizability of the results. Although we acknowledge that China is currently the biggest emerging economy, other emerging economies also exhibit impressive U-I knowledge creation and U-I knowledge commercialisation. Thus, future studies should aim to examine whether U-I collaboration activities carried out by other emerging economies foster their regional low carbon innovation performance development. Meanwhile, the data and sample constraints regarding our unit of analysis do not allow us to measure the effect of China's U-I knowledge creation and U-I knowledge commercialisation on low carbon innovation performance for specific enterprises. Future studies should examine whether those U-I collaboration activities diffuse advanced knowledge, R&D, and innovation capabilities to specific enterprises and across other units within the enterprises, thus enhancing the low carbon innovation performance of the specific industrial enterprise.

Reference

- Acs, Z.J., Anselin, L. and Varga, A., 2002. Patents and innovation counts as measures of regional production of new knowledge. *Research policy*, 31(7), pp.1069-1085.
- Aboelmaged, M. and Hashem, G., 2019. Absorptive capacity and green innovation adoption in SMEs: The mediating effects of sustainable organisational capabilities. *Journal of Cleaner Production*, 220, pp.853-863.
- Albort-Morant, G., Leal-Rodríguez, A.L. and De Marchi, V., 2018. Absorptive capacity and relationship learning mechanisms as complementary drivers of green innovation performance. *Journal of Knowledge Management*.
- Andersen, M.M., 2008, June. Eco-innovation—towards a taxonomy and a theory. In 25th celebration DRUID conference (pp. 17-20).

Aitken, B.J. and Harrison, A.E., 1999. Do domestic firms benefit from direct foreign investment? Evidence from Venezuela. *American economic review*, 89(3), pp.605-618.

Aiken, L.S., West, S.G. and Reno, R.R., 1991. *Multiple regression: Testing and interpreting interactions*. sage.

Andersson, M. and Karlsson, C., 2006. Regional innovation systems in small and medium-sized regions. In *The emerging digital economy* (pp. 55-81). Springer, Berlin, Heidelberg.

Arellano, M. and Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies*, 58(2), pp.277-297.

Arenal, A., Armuña, C., Feijoo, C., Ramos, S., Xu, Z. and Moreno, A., 2020. Innovation ecosystems theory revisited: The case of artificial intelligence in China. *Telecommunications Policy*, 44(6), p.101960.

Asheim, B.T., Boschma, R. and Cooke, P., 2011. Constructing regional advantage: Platform policies based on related variety and differentiated knowledge bases. *Regional studies*, 45(7), pp.893-904.

Audretsch, D.B. and Keilbach, M., 2007. The localisation of entrepreneurship capital: Evidence from Germany. *Papers in Regional Science*, 86(3), pp.351-365.

Awan, U., Arnold, M.G. and Gölgeci, I., 2021. Enhancing green product and process innovation: Towards an integrative framework of knowledge acquisition and environmental investment. *Business Strategy and the Environment*, 30(2), pp.1283-1295.

Barbieri, N., Marzucchi, A. and Rizzo, U., 2020. Knowledge sources and impacts on subsequent inventions: Do green technologies differ from non-green ones?. *Research Policy*, 49(2), p.103901.

Barnes, T., Pashby, I. and Gibbons, A., 2002. Effective university–industry interaction: A multi-case evaluation of collaborative r&d projects. *European Management Journal*, 20(3), pp.272-285.

Barley, W.C., Treem, J.W. and Kuhn, T., 2018. Valuing multiple trajectories of knowledge: A critical review and agenda for knowledge management research. *Academy of Management Annals*, 12(1), pp.278-317.

Becker, W. and Dietz, J., 2004. R&D cooperation and innovation activities of firms—evidence for the German manufacturing industry. *Research policy*, 33(2), pp.209-223.

Bekkers, R. and Freitas, I.M.B., 2008. Analysing knowledge transfer channels between universities and industry: To what degree do sectors also matter?. *Research policy*, 37(10), pp.1837-1853.

Bellini, E., Piroli, G. and Pennacchio, L., 2019. Collaborative know-how and trust in university–industry collaborations: Empirical evidence from ICT firms. *The Journal of Technology Transfer*, 44(6), pp.1939-1963.

Bettiol, M., De Marchi, V., Di Maria, E. and Grandinetti, R., 2013. Determinants of market extension in knowledge-intensive business services: Evidence from a regional innovation system. *European Planning Studies*, 21(4), pp.498-515.

Bjerregaard, T., 2010. Industry and academia in convergence: Micro-institutional dimensions of R&D collaboration. *Technovation*, 30(2), pp.100-108.

Blackler, F., 1993. Knowledge and the theory of organizations: Organizations as activity systems and the reframing of management. *Journal of management studies*, 30(6), pp.863-884.

Blundell, Richard, and Stephen Bond. "GMM estimation with persistent panel data: an application to production functions." *Econometric reviews* 19, no. 3 (2000): 321-340.

Boccanfuso, D., Larouche, A. and Trandafir, M., 2015. Quality of higher education and the labor market in developing countries: Evidence from an education reform in Senegal. *World development*, 74, pp.412-424.

Bruneel, J., d'Este, P. and Salter, A., 2010. Investigating the factors that diminish the barriers to university–industry collaboration. *Research policy*, 39(7), pp.858-868.

Caloghirou, Y., Giotopoulos, I., Kontolaimou, A., Korra, E. and Tsakanikas, A., 2021. Industry-university knowledge flows and product innovation: How do knowledge stocks and crisis matter?. *Research Policy*, 50(3), p.104195.

Caniëls, M.C. and Van den Bosch, H., 2011. The role of higher education institutions in building regional innovation systems. *Papers in Regional Science*, 90(2), pp.271-286.

Capó-Vicedo, J., Mula, J. and Capó, J., 2011. A social network-based organizational model for improving knowledge management in supply chains. *Supply Chain Management: An International Journal*.

Carayannis, E.G., Alexander, J. and Ioannidis, A., 2000. Leveraging knowledge, learning, and innovation in forming strategic government–university–industry (GUI) R&D partnerships in the US, Germany, and France. *Technovation*, 20(9), pp.477-488.

Chalmers, D.M. and Balan-Vnuk, E., 2013. Innovating not-for-profit social ventures: Exploring the microfoundations of internal and external absorptive capacity routines. *International Small Business Journal*, 31(7), pp.785-810.

Chen, J. and Wei, S. (2008) ‘University–Industry Collaboration, Knowledge Management and Enterprise Innovation Performance: An Empirical Study’, *Industry and Higher Education*, 22(5), pp. 275–287.

Chen, K., Zhang, C., Feng, Z., Zhang, Y. and Ning, L., 2022. Technology transfer systems and modes of national research institutes: evidence from the Chinese academy of sciences. *Research Policy*, 51(3), p.104471.

Chesbrough, H., Vanhaverbeke, W. and West, J. eds., 2006. *Open innovation: Researching a new paradigm*. Oxford University Press on Demand.

Cohen, W.M. and Levinthal, D.A., 1989. Innovation and learning: the two faces of R & D. *The economic journal*, 99(397), pp.569-596.

Cooke, P., Uranga, M.G. and Etxebarria, G., 1998. Regional systems of innovation: an evolutionary perspective. *Environment and planning A*, 30(9), pp.1563-1584.

Choi, S.B., Lee, S.H. and Williams, C., 2011. Ownership and firm innovation in a transition economy: Evidence from China. *Research Policy*, 40(3), pp.441-452.

CNIPA, 2018. https://www.cnipa.gov.cn/art/2018/9/7/art_53_117816.html

Cooke, P., 1992. Regional innovation systems: competitive regulation in the new Europe. *Geoforum*, 23(3), pp.365-382.

Cooke, P., Uranga, M.G. and Etxebarria, G., 1998. Regional systems of innovation: an evolutionary perspective. *Environment and planning A*, 30(9), pp.1563-1584.

Dangelico, R.M., Pontrandolfo, P. and Pujari, D., 2013. Developing sustainable new products in the textile and upholstered furniture industries: Role of external integrative capabilities. *Journal of Product Innovation Management*, 30(4), pp.642-658.

Di Maria, E., De Marchi, V. and Spraul, K., 2019. Who benefits from university–industry collaboration for environmental sustainability?. *International Journal of Sustainability in Higher Education*.

Du, L., Zhang, Z. and Feng, T., 2018. Linking green customer and supplier integration with green innovation performance: The role of internal integration. *Business Strategy and the Environment*, 27(8), pp.1583-1595.

Elia, G., Margherita, A. and Passiante, G., 2020. Digital entrepreneurship ecosystem: How digital technologies and collective intelligence are reshaping the entrepreneurial process. *Technological Forecasting and Social Change*, 150, p.119791.

Faems, D., Van Looy, B. and Debackere, K., 2005. Interorganizational collaboration and innovation: Toward a portfolio approach. *Journal of product innovation management*, 22(3), pp.238-250.

Ferraris, A., Santoro, G. and Dezi, L., 2017. How MNC's subsidiaries may improve their innovative performance? The role of external sources and knowledge management capabilities. *Journal of Knowledge Management*.

Ferreras-Méndez, J.L., Fernández-Mesa, A. and Alegre, J., 2019. Export performance in SMEs: The importance of external knowledge search strategies and absorptive capacity. *Management International Review*, 59(3), pp.413-437.

Flor, M.L., Cooper, S.Y. and Oltra, M.J., 2018. External knowledge search, absorptive capacity and radical innovation in high-technology firms. *European Management Journal*, 36(2), pp.183-194.

Freeman, C., 1995. The 'National System of Innovation' in historical perspective. *Cambridge Journal of economics*, 19(1), pp.5-24.

Fritsch, M., 2002. Measuring the quality of regional innovation systems: A knowledge production function approach. *International Regional Science Review*, 25(1), pp.86-101.

Fu, X., 2008. Foreign direct investment, absorptive capacity and regional innovation capabilities: evidence from China. *Oxford development studies*, 36(1), pp.89-110.

Gluch, P., Gustafsson, M. and Thuvander, L., 2009. An absorptive capacity model for green innovation and performance in the construction industry. *Construction Management and Economics*, 27(5), pp.451-464.

Griliches, Z., 1979. Issues in assessing the contribution of research and development to productivity growth. *The bell journal of economics*, pp.92-116.

Griliches, Z., 1998. Patent statistics as economic indicators: a survey. In *R&D and productivity: the econometric evidence* (pp. 287-343). University of Chicago Press.

Gujarati, D.N., Porter, D.C. and Gunasekar, S., 2012. *Basic econometrics*. Tata mcgraw-hill education.

Hamad, W.B., 2018. The role of ICT in knowledge management processes: A Review. *International Journal of Engineering Science*, 16373.

He, Z.L. and Wong, P.K., 2012. Reaching out and reaching within: A study of the relationship between innovation collaboration and innovation performance. *Industry and Innovation*, 19(7), pp.539-561.

Higón, D. A. (2012) ‘The impact of ICT on innovation activities: Evidence for UK SMEs’, *International Small Business Journal*, 30(6), pp. 684–699.

Hong, W. and Su, Y.S., 2013. The effect of institutional proximity in non-local university–industry collaborations: An analysis based on Chinese patent data. *Research Policy*, 42(2), pp.454-464.

Hou, B., Hong, J., Wang, H. and Zhou, C., 2019. Academia-industry collaboration, government funding and innovation efficiency in Chinese industrial enterprises. *Technology Analysis & Strategic Management*, 31(6), pp.692-706.

Hultman, N., Sierra, K. and Shapiro, A., 2012. Innovation and Technology for Green Growth. *OLD PROBLEMS, NEW SOLUTIONS*, p.31.

Iammarino, S., 2005. An evolutionary integrated view of regional systems of innovation: concepts, measures and historical perspectives. *European planning studies*, 13(4), pp.497-519.

Jiang, C.X., Yang, Q., Li, S. and Wang, Y., 2011. The moderating effect of foreign direct investment intensity on local firms' intangible resources investment and performance implications: A case from China. *Journal of International Management*, 17(4), pp.291-302.

Kergroach, S., Meissner, D. and Vonortas, N.S., 2018. Technology transfer and commercialisation by universities and PRIs: benchmarking OECD country policy approaches. *Economics of Innovation and New Technology*, 27(5-6), pp.510-530.

Kunapatarawong, R. and Martínez-Ros, E., 2016. Towards green growth: How does green innovation affect employment?. *Research Policy*, 45(6), pp.1218-1232.

Laranja, M., Uyarra, E. and Flanagan, K., 2008. Policies for science, technology and innovation: Translating rationales into regional policies in a multi-level setting. *Research policy*, 37(5), pp.823-835.

Lau, A.K. and Lo, W., 2015. Regional innovation system, absorptive capacity and innovation performance: An empirical study. *Technological Forecasting and Social Change*, 92, pp.99-114.

Li, G., Xue, Q. and Qin, J., 2022. Environmental information disclosure and green technology innovation: Empirical evidence from China. *Technological Forecasting and Social Change*, 176, p.121453.

Li, J., Strange, R., Ning, L. and Sutherland, D., 2016. Outward foreign direct investment and domestic innovation performance: Evidence from China. *International Business Review*, 25(5), pp.1010-1019.

Li, X., 2011. Sources of external technology, absorptive capacity, and innovation capability in Chinese state-owned high-tech enterprises. *World Development*, 39(7), pp.1240-1248.

Lin, C., Lin, P., Song, F.M. and Li, C., 2011. Managerial incentives, CEO characteristics and corporate innovation in China's private sector. *Journal of comparative economics*, 39(2), pp.176-190.

Liu, X., Hodgkinson, I.R. and Chuang, F.M., 2014. Foreign competition, domestic knowledge base and innovation activities: Evidence from Chinese high-tech industries. *Research policy*, 43(2), pp.414-422.

Liu, Y., Yao, C., Wang, G. and Bao, S., 2011. An integrated sustainable development approach to modeling the eco-environmental effects from urbanization. *Ecological Indicators*, 11(6), pp.1599-1608

Lorenz, R., Benninghaus, C., Friedli, T. and Netland, T.H., 2020. Digitization of manufacturing: the role of external search. *International Journal of Operations & Production Management*.

Malerba, F., Orsenigo, L. and Peretto, P., 1997. Persistence of innovative activities, sectoral patterns of innovation and international technological specialization. *International Journal of Industrial Organization*, 15(6), pp.801-826.

Maravilhas, S. and Martins, J., 2019. Strategic knowledge management in a digital environment: Tacit and explicit knowledge in Fab Labs. *Journal of business research*, 94, pp.353-359.

Marzucchi, A. and Montresor, S., 2017. Forms of knowledge and eco-innovation modes: Evidence from Spanish manufacturing firms. *Ecological Economics*, 131, pp.208-221.

Mazzucchelli, A., Chierici, R., Tortora, D. and Fontana, S., 2021. Innovation capability in geographically dispersed R&D teams: The role of social capital and IT support. *Journal of Business Research*, 128, pp.742-751.

Meng, D., Li, X. and Rong, K., 2019. Industry-to-university knowledge transfer in ecosystem-based academic entrepreneurship: Case study of automotive dynamics &

control group in Tsinghua University. *Technological Forecasting and Social Change*, 141, pp.249-262.

Messeni Petruzzelli, A. and Murgia, G., 2020. University–Industry collaborations and international knowledge spillovers: a joint-patent investigation. *The Journal of Technology Transfer*, 45(4), pp.958-983.

Miao, C.L., Duan, M.M., Zuo, Y. and Wu, X.Y., 2021. Spatial heterogeneity and evolution trend of regional green innovation efficiency--an empirical study based on panel data of industrial enterprises in China's provinces. *Energy Policy*, 156, p.112370.

MOST, 2019.
<http://www.most.gov.cn/xxgk/xinxifenlei/fdzdgknr/kjtjbg/kjtj2021/202106/P020210608355573563342.pdf>

Mukhtarova, K.S., Trifilova, A.A. and Zhidbekkyzy, A., 2016. Commercialization of green technologies: An exploratory literature review. *Journal of International Studies*, 9(3).

Müller, J.M., Buliga, O. and Voigt, K.I., 2021. The role of absorptive capacity and innovation strategy in the design of industry 4.0 business Models-A comparison between SMEs and large enterprises. *European Management Journal*, 39(3), pp.333-343.

Munari, F., Rasmussen, E., Toschi, L. and Villani, E., 2016. Determinants of the university technology transfer policy-mix: A cross-national analysis of gap-funding instruments. *The Journal of Technology Transfer*, 41(6), pp.1377-1405.

Muscio, A. and Vallanti, G., 2014. Perceived obstacles to university–industry collaboration: Results from a qualitative survey of Italian academic departments. *Industry and Innovation*, 21(5), pp.410-429.

Nelson, R.R. ed., 1993. *National innovation systems: a comparative analysis*. Oxford University Press on Demand.

Neter, J. and Godfrey, J., 1985. Robust Bayesian Bounds for Monetary-Unit Sampling in Auditing. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 34(2), pp.157-168.

Nguyen, T. and Burgess, S., 2014. A case analysis of ICT for knowledge transfer in small businesses in Vietnam. *International Journal of Information Management*, 34(3), pp.416-421.

Ning, L. and Guo, R., 2022. Technological Diversification to Green Domains: Technological Relatedness, Invention Impact and Knowledge Integration Capabilities. *Research Policy*, 51(1), p.104406.

Nsanzumuhire, S.U. and Groot, W., 2020. Context perspective on University-Industry Collaboration processes: A systematic review of literature. *Journal of cleaner production*, 258, p.120861.

Ollo-López, A. and Aramendía-Muneta, M.E., 2012. ICT impact on competitiveness, innovation and environment. *Telematics and Informatics*, 29(2), pp.204-210.

Østergaard, C.R. and Drejer, I., 2022. Keeping together: Which factors characterise persistent university–industry collaboration on innovation?. *Technovation*, 111, p.102389.

Ouyang, P. and Fu, S., 2012. Economic growth, local industrial development and inter-regional spillovers from foreign direct investment: Evidence from China. *China Economic Review*, 23(2), pp.445-460.

Pacheco, L.F., Altrichter, M., Beck, H., Buchori, D. and Owusu, E.H., 2018. Economic Growth as a Major Cause of Environmental Crisis: Comment to Ripple et al. *Bioscience*, 68(4), pp.238-238.

Perkmann, M., Tartari, V., McKelvey, M., Autio, E., Broström, A., D’este, P., Fini, R., Geuna, A., Grimaldi, R., Hughes, A. and Krabel, S., 2013. Academic engagement and

commercialisation: A review of the literature on university–industry relations. *Research policy*, 42(2), pp.423-442.

Perkmann, M. and Walsh, K., 2009. The two faces of collaboration: impacts of university-industry relations on public research. *Industrial and Corporate Change*, 18(6), pp.1033-1065.

Petruzzelli, A.M., 2011. The impact of technological relatedness, prior ties, and geographical distance on university–industry collaborations: A joint-patent analysis. *Technovation*, 31(7), pp.309-319.

Ramaciotti, L. and Rizzo, U., 2015. The determinants of academic spin-off creation by Italian universities. *R&D Management*, 45(5), pp.501-514.

Rantala, T. and Ukko, J., 2019. Performance evaluation to support European regional development—A university–industry perspective. *European Planning Studies*, 27(5), pp.974-994.

Rajalo, S. and Vadi, M., 2017. University-industry innovation collaboration: Reconceptualization. *Technovation*, 62, pp.42-54.

Ripple, W.J., Wolf, C., Newsome, T.M., Galetti, M., Alamgir, M., Crist, E., Mahmoud, M.I., Laurance, W.F. and 15,364 Scientist Signatories from 184 Countries, 2017. World scientists' warning to humanity: a second notice. *BioScience*, 67(12), pp.1026-1028.

Robertson, J., McCarthy, I.P. and Pitt, L., 2019. Leveraging social capital in university-industry knowledge transfer strategies: a comparative positioning framework. *Knowledge Management Research & Practice*, 17(4), pp.461-472.

Rui, H. and Yip, G.S., 2008. Foreign acquisitions by Chinese firms: A strategic intent perspective. *Journal of world business*, 43(2), pp.213-226.

Scandura, A., 2016. University–industry collaboration and firms' R&D effort. *Research Policy*, 45(9), pp.1907-1922.

Shaw, G. and Williams, A., 2009. Knowledge transfer and management in tourism organisations: An emerging research agenda. *Tourism management*, 30(3), pp.325-335.

Sjöö, K. and Hellström, T., 2019. University–industry collaboration: A literature review and synthesis. *Industry and higher education*, 33(4), pp.275-285.

Shi, X., Wu, Y. and Fu, D., 2020. Does University-industry collaboration improve innovation efficiency? Evidence from Chinese firms[♦]. *Economic Modelling*, 86, pp.39-53.

Slavtchev, V. and Göktepe-Hultén, D., 2016. Support for public research spin-offs by the parent organizations and the speed of commercialization. *The Journal of Technology Transfer*, 41(6), pp.1507-1525.

Spithoven, A., Clarysse, B. and Knockaert, M., 2010. Building absorptive capacity to organise inbound open innovation in traditional industries. *Technovation*, 30(2), pp.130-141.

Steffen, W., Richardson, K., Rockström, J., Cornell, S.E., Fetzer, I., Bennett, E.M., Biggs, R., Carpenter, S.R., De Vries, W., De Wit, C.A. and Folke, C., 2015. Planetary boundaries: Guiding human development on a changing planet. *Science*, 347(6223), p.1259855.

Tang, K., Qiu, Y. and Zhou, D., 2020. Does command-and-control regulation promote green innovation performance? Evidence from China's industrial enterprises. *Science of the Total Environment*, 712, p.136362.

Wang, D., Zhou, T., Lan, F. and Wang, M., 2021. ICT and socio-economic development: Evidence from a spatial panel data analysis in China. *Telecommunications Policy*, 45(7), p.102173.

Wang, Z., He, Q., Xia, S., Sarpong, D., Xiong, A. and Maas, G., 2020. Capacities of business incubator and regional innovation performance. *Technological Forecasting and Social Change*, 158, p.120125.

Yang, H., Li, L. and Liu, Y., 2022. The effect of manufacturing intelligence on green innovation performance in China. *Technological Forecasting and Social Change*, 178, p.121569.

Yi, L., Wang, Y., Upadhaya, B., Zhao, S. and Yin, Y., 2021. Knowledge spillover, knowledge management capabilities, and innovation among returnee entrepreneurial firms in emerging markets: Does entrepreneurial ecosystem matter?. *Journal of Business Research*, 130, pp.283-294.

Zhao, N., Liu, X., Pan, C. and Wang, C., 2021. The performance of green innovation: From an efficiency perspective. *Socio-Economic Planning Sciences*, 78, p.101062.

Zhou, F., He, Y., Ma, P. and Mahto, R.V., 2020. Knowledge management practice of medical cloud logistics industry: transportation resource semantic discovery based on ontology modelling. *Journal of Intellectual Capital*.

Zhou, R. and Tang, P., 2020. The role of university Knowledge Transfer Offices: Not just commercialize research outputs!. *Technovation*, 90, p.102100.

Zhang, J., Liang, G., Feng, T., Yuan, C. and Jiang, W., 2020. Green innovation to respond to environmental regulation: How external knowledge adoption and green absorptive capacity matter?. *Business Strategy and the Environment*, 29(1), pp.39-53.