Regional Studies

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/cres20

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REGIONAL STUDIES
https://doi.org/10.1080/00343404.2021.1954610

Routledge Taylor & Francis Group
RSA Regional Studies Association

A data-driven global innovation system approach and the rise of China's artificial intelligence industry

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ABSTRACT

Building upon the global innovation system (GIS) framework, this paper develops an analytical approach to incorporate data as a foundation-level resource in data-driven innovation systems and to unravel how the interplay of system resources' spatial characteristics, multi-scalar institutions and actor strategies leads to the emergence of China's artificial intelligence industry. China's loose institutional regime significantly facilitates the formation of the market, legitimacy and data, while entrepreneurs and digital platforms are the key actors coupling system resources to China's innovation system. As data become a critical resource, actors controlling data develop institutional power to shape the formation of the data-driven industry.

KEYWORDS
emerging industry; artificial intelligence; global innovation system; data-driven innovation; China

JEL L86, O33
HISTORY Received 20 December 2019; in revised form 15 June 2021

INTRODUCTION

Since the phenomenal victory of AlphaGo over human players in 2016, artificial intelligence (AI) has become the most eye-catching technology globally. As a general-purpose technology, AI has been deployed in various sectors, showing huge potential in boosting economic development and addressing global sustainable development challenges. Although AI advancements have sparked widespread ethical concerns such as job replacement, loss of accountability, algorithmic bias and privacy violations (Butcher & Beridze, 2019), many countries have rolled out their AI strategies to secure an advantageous position in the new round of industrial revolution. In addition, thousands of companies engaged in AI technology development have sprung up around the world, forming an emerging AI industry (Xue et al., 2018). Though still in its formative stage, an AI value chain, including AI infrastructure providers (e.g., in computing chips and sensors), technology developers (e.g., in computer vision and voice recognition), and application scenarios (e.g., in autonomous driving and smart healthcare), has been formed.

AI is a typical data-driven innovation as it feeds on data (Klingenberg et al., 2019). The AI we are discussing today mostly refers to machine learning, which relies on data to train algorithms to predict and make decisions (Haenlein & Kaplan, 2019). More data means more accuracy and more technological competencies. Therefore, data have been widely valued as the 'new oil' in the age of AI (Parkins, 2017); and it is not surprising that digital platforms such as Google, Amazon and Facebook are at the global frontier of AI technology development. Data are increasingly critical not only for business value creation but also for knowledge development and policymaking (Yu et al., 2021). Those who possess the capacity to collect, analyse and utilize large amounts of data will gain tremendous competitive advantages. However, exploiting data is a trade-off between value creation and risk control (Abraham et al., 2019). Too little data regulation will damage users' benefits, while too much data protection will discourage firms from using data to innovate (Agrawal et al., 2019). Therefore, a country's data regime will significantly shape the development of data-driven innovations in its territory.

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Accompanying the rising impact of AI and data is a shift in the global industrial competitive landscape, in which China has been one of the leading players in the AI industry. China has hosted the world's second-largest cluster of AI firms (Xue et al., 2018). At the subnational level, Beijing, Shanghai, Shenzhen and Hangzhou have been global hotspots where AI firms emerge and aggregate. In addition, pervasive applications of AI in various scenarios are mushrooming in China. The objective of this paper is to reveal how this controversial data-driven industry emerges in China. Observers have mainly attributed it to China's huge market and rich data (e.g., Ding, 2018), but what has been largely neglected are China's social and institutional contexts that give rise to these resources and the role of heterogeneous actors in coupling these resources.

Recent literature has argued that local new path creation is a process of aligning and coupling endogenous and extra-regional system resources, particularly knowledge, financial investment, market and legitimacy (Binz et al., 2016). The latest development in the global innovation system (GIS) approach by Binz and Truffer (2017) offers a strong framework with which to understand where these system resources are formed and how they affect different industry formations in different places. GIS contends that due to the differences in innovation modes and valuation modes, the extent and form of international interdependencies will significantly vary in different industries, resulting in diverse development pathways over space (Binz et al., 2020). The system resources of an emerging industry may be generated at different spatial scales, conditioned by multi-scalar institutions. However, the existing literature fails to reveal through whose agency these system resources are created, mobilized and coupled into certain places. Although many studies have highlighted the role of entrepreneurs in coupling system resources (e.g., Zhang & White, 2016), less knowledge has been developed about how actors shape the changing institutional environment of emerging industries (Battilana et al., 2009; Yap & Truffer, 2019). Additionally, innovation system approaches have paid little attention to the role of data as a critical resource in data-driven innovation systems, which is increasingly problematic since the world is becoming increasingly digitalized (Weber & Truffer, 2017).

Responding to these gaps, this paper proposes a modified GIS approach to understand the emergence of data-driven innovations. We differentiate two levels of system resources in data-driven innovation systems: data as the foundation-level resource and knowledge, investment, market, and legitimacy as system function-level resources. We then articulate how data matter in the formation of function-level resources. We argue that system resources in data-driven industries have different GIS spatial characteristics, conditioned by multi-scalar institutions, and actors couple these system resources into a place by leveraging sticky resources and shaping the changing institutions, especially those regarding data.

The remainder of the paper is structured as follows. The next section provides a literature review and develop a modified GIS approach to understand why and how data-driven industries emerge in certain places. The third section describes the methodology. The fourth section elaborates on the emergence of the AI industry in China with our new conceptual approach. The fifth section discusses the results. The final section concludes.

THEORETICAL BACKGROUND AND CONCEPTUAL APPROACHES

Emerging industries and GIS

Emerging industries are newly formed or reformed industries that are induced by technological innovations, new consumer needs, or other economic and sociological changes (Porter, 2008). Economic geography has been particularly interested in why new industries arise in some places but not in others. Institutional economic geography argues that a place's institutional structure possesses the main causal power (Martin, 2000) while evolutionary economic geography (EEG) highlights the role of existing local competencies in influencing the emergence of new industries (Boschma & Frenken, 2011). However, EEG has largely overlooked the extra-regional relations that actors may use to anchor resources for local new path creations. Relational economic geography has shifted the focus to the role of multi-scalar actor relations in explaining spatial outcomes (Boggs & Rantisi, 2003), but it risks downplaying internal territorial interests and constraints in influencing territorial politics (Jonas, 2012).

Innovation system approaches have also shed much light on the emergence of new industries (Weber & Truffer, 2017). The technological innovation system (TIS) approach highlights the interaction between actors, networks and institutions in the generation, diffusion and utilization of new technologies (Bergek et al., 2008). Recent TIS studies focus on system functions or processes such as entrepreneurial experiments, knowledge development, market formation, resource mobilization and legitimization (Bergek et al., 2008; Hekkert et al., 2007). However, TIS studies still offer little understanding about what and who drives the formation and evolution of system functions (Kern, 2015).

Drawing insights from economic geography and innovation system research, Binz et al. (2016) argue that local new path creation is a process of aligning distantly distributed relevant resources and anchoring them to local innovation systems. These relevant resources are condensed into four distinct key resources: knowledge, niche markets, financial investment and legitimacy. While mounting research has shown the importance of knowledge in new industry formation, the processes for market valuation have received less attention. A niche market is critical for emerging industries because it provides a protected space for new products to compete with existing technologies. New technologies also have to overcome the liability of newness (Zhang & White, 2016), and legitimacy is an important resource for them to align with pre-existing institutional structures and reduce diffusion barriers. Finally, investment is not only important in providing scarce financial resources but also pivotal in the sense that it could be viewed as the anticipation of future market formation and legitimation processes and thus reduces uncertainties (Binz et al., 2016).

As innovation is increasingly globalized, the conventional hypothesis that system resources only develop within specific territorial boundaries is severely challenged. The allure of the GIS framework developed by Binz and Truffer (2017) lies in its strength in explaining where and how an industry's system resources are formed and coupled from a multi-scalar perspective. GIS advocates that some system resources are highly sticky to local contexts whereas others are more mobile and transferable in space, depending on the industry's GIS typologies, which are identified based on the industry's innovation mode and valuation mode. In the technological innovation dimension, an industry can be dominated by either a science and technology-driven innovation (STI) mode or a doing, using and interacting (DUI) mode. In the STI mode, knowledge is usually science based and codified and thus more mobile through internationalized networks. In contrast, knowledge learning in the DUI mode is more experience based and tacit, requiring close interactions within certain geographical boundaries. In the valuation dimension, some products are very standardized across global markets while others are more customized to specific local contexts. Markets, investment and legitimacy are more mobile in a standardized scenario, and actors in one place could easily obtain access to these resources created in distant places. In a customized valuation scenario, however, these resources are closely associated with localized user needs, institutional settings and technological opportunities; and it is costly for extra-regional actors to transfer them to other territorial innovation systems.

The combination of these two dimensions differentiates four generic GIS configurations, namely footloose, market-anchored, production-anchored and spatially sticky. In a footloose GIS (e.g., smartphone), both the innovation mode and valuation mode are characterized by high mobility, and all system resources are rather mobile at the global level. By contrast, innovations and valuation in a spatially sticky GIS are sticky to local contexts (e.g., luxury watchmaking), and the formation of system resources is highly rooted in particular places. In a market-anchored GIS (e.g., personalized medicine), knowledge and financial investment are rather footloose, but market and legitimacy are spatially sticky. The opposite is true in the production-anchored GIS (e.g., furniture).

A main takeaway from the GIS framework is that one needs to consider an industry's GIS characteristics and the corresponding resource mobility over space when examining its emergence in certain places. Although not expressed explicitly, the GIS literature also points to the crucial role of multi-scalar institutions in defining the characteristics of system resources and hence the formation of GIS types. For instance, the characteristics of the valuation mode and its related system resources (e.g., market, investment and legitimacy) are often contingent on institutional contexts. In a specific GIS type, whereas some resource formations are mainly conditioned by local institutions, others are more subject to international level institutions. Besides, institutions also shape actors' agency and networks in aligning, mobilizing and anchoring system resources.

Role of actors in resource mobilization and institutional change

However, the GIS framework still misses a part to capture the rise of emerging industries, and we believe this is where actor strategies should be considered. New path creations entail actors' strategic agency not only in mobilizing resources but also in unlocking incumbent structures (Karnøe & Garud, 2012). There have been attempts to map how actors leverage their multi-scalar relations to align and couple system resources to local innovation systems (Binz et al., 2016; Yu & Gibbs, 2020). However, GIS research has not paid sufficient attention to how actors affect resource formation by shaping institutional environments. In this aspect, the institutional entrepreneurship literature has provided many insights (e.g., Battilana et al., 2009; Grillitsch, 2019). To serve the interests they value highly, entrepreneurs not only can utilize opportunities in existing markets (ordinary discovery) but also destroy the stability of existing institutions and create rules favouring their future business (extraordinary discovery) (Yu, 2001). In fields such as emerging industries where the institutional setting is still very much in the making, entrepreneurs are expected to play a more critical role in institution formation (Gong & Hassink, 2019; Yap & Truffer, 2019). Particularly, actors who control a broad range of critical resources will exert a considerable impact on the institutional structure of an innovation system at the formation stage (Markard & Truffer, 2008).

Therefore, to understand the emergence of an industry in a particular place, one should examine the interaction between the industry's GIS characteristics, multi-scalar institutions and local actor strategies. Each resource formation in different GIS types has different spatial scopes and thus is conditioned by institutions at different scales, which also shape and are shaped by actor actions. The emergence of a new industry in a place needs actors' strategies not only in coupling endogenous and extra-regional resources but also in shaping a favourable selection environment to sustain the infant industry.

A modified GIS approach for data-driven innovations

Another gap in the GIS literature becomes increasingly prominent when it comes to the era of Industry 4.0, where many innovations rely on data to offer new products and services (Klingenberg et al., 2019). Data-driven innovations entail the exploitation of data to create value through the data value chain, including data acquisition, data analysis, data curation, data storage and data usage (Curry, 2016). Consequently, data-driven innovation systems involve more data-related actors such as data suppliers, data users, data marketplaces and data regulators.

Though often called the 'new oil', data have several distinct features from fossil fuels. First, data can be acquired, stored and transferred at a very low cost (Klingenberg et al., 2019). Second, data are rarely exhausted and are non-rival in the sense that they can be used by different users simultaneously. However, it is very challenging to define the ownership of data because they are usually co-produced, and one individual's behavioural data often contain information of others (Weber, 2017). Third, data can be used for a much wider range of purposes, connecting artefacts, business and people in a cyber–physical system (Klingenberg et al., 2019). Finally, due to the network scale effect and winner-takes-all effect of the platform economy, valuable data are usually aggregated to a few giant digital platforms, which can develop formidable power to influence the development of digital economies (Kenney & Zysman, 2016).

In data-driven innovation systems, data are the key resource not only because they are the foundational input but also because they are the trigger factor for the entire innovation process (Trabucchi & Buganza, 2019). Data are a critical material from which knowledge can be extracted in modern scientific discovery (Curry, 2016). The explosion of available data is not only feeding advanced data-mining technologies but also generating new insights about the world. For business, big data allows companies to better know customers' ideas and preferences and to profit from them by exploiting unmet demand or providing personalized products (Bresciani et al., 2021; Saura et al., 2021). This facilitates entrepreneurial experiments and market formation. In many data-driven innovations, data exist at the very beginning of the innovation process and also represent the final product at the end of the process (Trabucchi & Buganza, 2019). In their survey of machine learning start-ups, Hartmann and Henkel (2018) find that having valuable, rare, inimitable and non-substitutable data is the key factor in acquiring venture capital funding. Data are also increasingly important in the public policy process, including agenda setting, policy formulation, decision-making, policy implementation and policy evaluation, with more efficiency and accuracy (Valle-Cruz et al., 2020).

Given these observations, we propose a modified GIS approach to incorporate data as a foundation-level system resource in data-driven innovation systems in which data enable the formation of knowledge, investment, market and legitimacy at the functional level. Similar to the function-level resources, data also have GIS spatial patterns. The formation of data is significantly conditioned by institutions, which decide whether, how and what data can be collected, transferred and utilized; who owns data; and how the revenue from data will be distributed. Furthermore, actors apply various strategies to produce, collect and exploit data for knowledge creation, market formation and investment mobilization. Therefore, to map the geography of a specific data-driven industry in a specific place, we need to examine the spatial mobility of data and its relations with other system resources and investigate how relevant institutions and local actors shape the formation and mobilization of these resources.

METHODS AND DATA

Global AI research began in the 1950s, but it is not until the early 2010s that AI can be commercially applied due to the breakthroughs in algorithms (deep learning in particular), computing power and data. Nonetheless, current AI development is still at the stage of narrow AI, which only outperforms humans in a single capability in specific tasks. The AI industry is a group of firms that develop machine systems (including algorithms and hardware) that mimic human intelligence to solve particular problems. These firms include not only start-ups that develop and sell AI as a core product but also incumbent firms that use AI to complement their main businesses. China has fostered a relatively large AI cluster and accumulated certain technology advances and an evident advantage in applications (Xue et al., 2018). Applying the above conceptual approach, this paper investigates how the interplay of the spatial characteristics of data and other system resources, multi-scalar institutions and actor strategies leads to the formation of the AI industry in China. It should be noted that GIS typology mainly maps the spatial characteristics of an industry's core activities instead of the entire value chain, which could contain various complex innovation modes and valuation modes. This paper mainly focuses on the firms that develop and commercialize AI algorithms.

From June 2018 to May 2020, 66 semi-structured interviews were conducted with AI enterprises, government agencies, universities, industry associations and research institutions in China (one in the UK). These interviews include three topics designed to address this research objective:

- What factors facilitate or obstruct China's AI industry?
- How are resources distributed and how do they flow within the AI innovation system?
- How do different actors respond to the emergence of AI and its consequent changes?

In most of these interviews, we managed to talk to respondents from the top management level and gather in-depth observations from industry experts. These interview materials are supplemented and triangulated by many secondary industry reports, government documents, news reports and expert forums. Interviewees were anonymized in our result presentation and numbered by the type of organization, for example, enterprise (ET), university (UV), research institute (RI), industry association (IA) and government (GV), and the sequence of interviews (e.g., ET01).

Result: the emergence of the AI industry in China

China started its AI research in the early 1980s, but achieved only incremental progress in the following three decades. While technological development was struggling, another pillar of AI, data, was growing rapidly. Since the early 2000s, the fast deployment of information and communication technology (ICT) infrastructure, low labour costs and the large scale of internet users have facilitated China to become one of the leading countries in the internet economy. Some digital platforms such as Baidu, Alibaba and Tencent ('BAT') have grown to be the most valuable companies in the world. When deep learning algorithms matured in the early 2010s, this window of opportunity was soon seized by China's digital giants and new start-ups by leveraging China's rich data and application scenarios. Among others, image recognition and intelligent recommendation have been the two most successfully commercialized AI technologies. While AI technology developers actively apply AI to various application scenarios such as traffic control, retailing and healthcare ('AI+'), traditional sectors are also enthusiastically using AI to upgrade their businesses ('+AI'), which in turn provides more data and sector-specific knowledge for AI technology improvement. This positive feedback loop among data, technology, investment and market drives China's AI industry development.

However, this infant industry is also suffering a liability of newness. Though widely believed to be a promising technology, AI has not brought revenue to most AI companies so far. Most applications are in their initial stages, and mature business models need to be developed (ET05; ET57). Besides the heated debates on AI's impact on employment, the 'black box' nature of AI has raised wide concern on AI discrimination (Haenlein & Kaplan, 2019). Furthermore, there are criticisms that the development of the AI industry may cost citizens' privacy. Therefore, legitimacy is urgently needed for the development of this controversial industry. In this section we present how the interaction between GIS characteristics, multi-scalar institutions and actors' strategies leads to the formation of China's AI industry. We illustrate how data matter in system function-level resource formation and then proceed to the foundational level to examine the spatial pattern of data and the institutions and actor strategies underlying this pattern.

THE FORMATION OF SYSTEM FUNCTION-LEVEL RESOURCES

Knowledge: footloose

Current AI technology is largely science driven (STI), and its knowledge base is highly codified and footloose. Initially started in a few lighthouse universities, deep learning research gained rapid development within academic circles and industry through joint research, scientific publications and talent mobility (Benaich & Hogarth, 2020). In this process, shared databases among academics (e.g., ImageNet), academic communications (e.g., AI conferences) and the global open-source movement played important roles. ImageNet was established by scientists from Stanford University in 2009 and soon became the largest image recognition database in the world. It provided free labelled images for algorithm developers around the world. Furthermore, algorithm developments were facilitated by open-source communities such as GitHub, where developers shared codes with new ideas and data. Since 2015, technology giants such as Google, Facebook and IBM have established open-source platforms for AI algorithm development. The main rationale for this movement was to accumulate more data to train better algorithms (ET09).

In this context, Chinese universities and research institutes were actively committed to AI research through international collaboration and the establishment of specialized AI schools or labs. In 2018, 53% of China's highly cited AI papers were published through international collaboration (Xue et al., 2018). China has become the global leader in terms of the number of AI papers and patents, but it still faces a severe shortage of breakthrough ideas and top talents. Many small Chinese AI companies mainly chose to build upon existing open-source algorithms and achieved incremental technological development by combining sector-specific knowledge and data (ET09; ET43; UV14). In addition to collaborating with domestic universities, large companies spent huge efforts recruiting overseas AI talent, especially Chinese AI scientists from the United States. China has received 17% of American-educated AI doctoral students who leave the United States after graduation, and 40% of them enter the industry (Benaich & Hogarth, 2020). Many AI start-ups were established by returnee scientists or researchers with research experience in American AI labs (ET05; ET08; ET25; ET35; ET44; ET57). In particular, talent spillovers and spin-offs from Microsoft Research Asia have played a very important role in the rise of many Chinese AI companies (ET25; RI33). Besides, Chinese AI companies energetically sought to bring in knowledge through, for example, funding research centres abroad (mainly in the United States), collaboration with top universities and acquisitions of overseas AI firms.

The AI industry has started to play an increasingly important role in AI knowledge development because it possesses computing power, data and application scenarios. Digital giants have attracted a large number of researchers from academia and built many ivory tower-like research institutes for researchers to explore and publish AI knowledge. An increasing number of AI papers have been published by AI enterprises, especially in top academic conferences (ET35). Gradually, several Chinese digital giants and AI unicorns have also become important knowledge contributors in global open-source platforms, especially in voice recognition and computer vision (ET07; ET35). Some companies such as Baidu, Sense Time and Magvii have also established their open-source platforms. Overall, China's AI industry seeks to anchor global AI knowledge through international collaborations, acquisitions and attracting top AI talent, on the one hand, and to improve its role in global AI knowledge generation by leveraging China's data and application-specific knowledge and engaging in more basic research, on the other.

Financial investment: footloose

Financial investment in the AI industry is relatively footloose. Since 2013, the global AI industry has received steadily increasing investment. In 2017, global AI investment reached US$39.5 billion, with China alone representing 70% of this total (Xue et al., 2018). Both foreign and domestic investors had a strong faith that China's huge market and rich data would bring high investment returns (ET05; ET25; ET44). The interplay between investment, market and data drove China's AI industry to a fast track. The growth of Sense Time is a typical example. Before the establishment of Sense Time, Tang Xiao'ou, its founder, led a world-leading research team in face-recognition algorithms at the Chinese University of Hong Kong, but was trapped by limited data and computing capacity. The situation soon changed when IDG, a Boston-based venture capital, invested in Tang Xiao'ou's team and built Sense Time in 2014. Subsequent investors such as Star VC and Qualcomm also helped Sense Time recruit top AI talent and build one of the largest computing platforms in Asia. Sense Time's technologies then soon penetrated various sectors, which in turn enabled Sense Time to build a huge image database. With this virtuous feedback loop, venture capital kept investing in this company, making it one of the world's most valuable AI unicorns (ET35).

Notably, most of China's AI start-ups received investments from large digital platforms, especially BAT. An AI entrepreneur observed the following: 'This industry, if does not belong to A [Alibaba], then it must belong to T [Tecent] or B [Baidu]. Almost every new AI firm has some connections with BAT' (ET08). Realizing the strategic importance of applications and data, both digital giants and emerging AI unicorns strived to build their business ecosystem by investing in new AI application firms. The chief executive officer of an AI unicorn stated the following: 'if you want to grow bigger, you need to have your technologies applied in various sectors. Our investment fund has invested in 14 firms, and we plan to invest in 20 firms annually' (ET07).

As the industry was in the process of being defined, there were also many firms 'using the name of AI to get investments but only selling conventional products' (ET06). Additionally, the majority of China's AI investment was mobilized to the application side. Nonetheless, as China's market demand for specialized AI chips grew rapidly, venture capital began to increase investment in Chinese AI chip companies. Particularly, after the US chip embargo on Chinese companies in 2018, the Chinese government decided to strongly support the indigenous chip industry, and investors began to invest more in AI chips (ET44). Additionally, realizing the strategic importance of the AI industry in future regional competition, local governments were actively attracting AI companies and talent to their jurisdictions with favourable financial support, such as government venture capital funds and lower taxes and rents.

Market: spatially sticky

AI markets are highly contingent on place contexts and sectoral specificities. The application of AI technologies should be adapted to specific use scenarios (e.g., a hospital). The relatively backward status of China's traditional sectors provided a huge market window for AI applications. In the healthcare scenario, for example, the shortage of highly skilled doctors in identifying diseases such as cancer was very acute (ET05; ET24). These scenarios thus had a strong interest in using AI technologies to improve accuracy and efficiency, which was facilitated by China's lax regulations on market entry. Many application sectors in China have not developed high standards on ethics and safety or otherwise not strictly implemented them. A returnee entrepreneur from the US explained his rationale for engaging in AI healthcare in China: 'the American healthcare market is very mature but slow in accepting new products … they have many rigid regulations in this sector, but China has much fewer regulations, and hospitals are more willing to adopt new technologies' (ET05). Similar stories occurred in other sectors such as finance, retailing, transportation and education. However, these application markets were very segmented, and in many cases, close relationships ('*guanxi*') with adopters affected whether or how a technology developer could enter the scenarios (ET57; ET58).

Both governments and private sectors played important roles in China's AI market formation. In particular, the public security bureaus' large demand for detecting criminals opened the first niche market for AI technologies (ET09; ET18). Many local governments have provided procurements for AI services in traffic control and smart-city projects. They also supported the industry by, for example, providing AI demonstration projects and subsidizing AI technology adopters in sectors such as healthcare, education, transportation and manufacturing (GV03; ET29; ET34).

AI technology developers and digital platforms were energetically seeking to enter various application scenarios ('AI+') to gain access to both market and data, which in turn improved their technological competencies. An AI entrepreneur stated the following: 'We have a team working in a hospital every day to learn doctors' needs and gain patients' data to improve our technology. After half a year, the accuracy rate has risen from 85% to 95%' (ET45). Many downstream application firms also sought to develop their own AI technologies to better profit from their data and relations with consumers ('+AI'). Additionally, an increasing number of AI firms strived to enter international markets. Some technology developers adapted their technology competence developed in China to other countries' application markets (ET18; ET35; ET60), some chose to collaborate with world-known international companies (ET29), and some sought to enter areas that are less controversial such as goods recognition (ET25).

Legitimacy: spatially sticky

AI is a very controversial technology, but it has different legitimacy in different contexts. For instance, while some Western countries and regions have banned face recognition, Chinese society emphasizes its positive virtues over its risks. Since the Reform and Opening Up, 'development is of overriding importance' has been one of the dominant development philosophies in China. Despite much improvement in recent years, Chinese society still pays insufficient attention to the social risks accompanying economic development in comparison with Western countries. Moreover, as many indigenous innovations (e.g., high-speed trains, mobile payments and bike-sharing) benefit people's daily lives, technological innovations were given a 'halo' by Chinese society. Regarding AI specifically, Chinese citizens showed a high level of tolerance to AI's social risks. According to a survey by Xue et al. (2018), only 2.4% of respondents were against the development of AI in China. Trust in technologies and technology users, particularly the government, mattered here. For instance, when discussing face-recognition technology, an AI researcher expressed his opinion: 'as a citizen, I do know that some of my information is being collected, but I don't worry at all that my data will be used maliciously' (RI38).

In 2017, China's central government implemented the Development Plan for the Next Generation Artificial Intelligence, aiming to build China as a global AI innovation hub by 2030. The strategic focus of China's AI strategy is to promote its economic development, international competition, social governance and moral governance (Roberts et al., 2020). Since 2018, the Ministry of Science and Technology (MOST) has launched 15 National AI Open Innovation Platforms, covering a wide range of fields from computing infrastructure to sectoral applications, led by leading digital platforms and AI players. It also initiated AI pilot zones to encourage cities to accelerate various AI applications and conduct AI-based policy experiments. At the local level, most regional governments saw AI as an important lane for economic development and supported the industry with various favourable policies (GV02; IA03; GV50; GV51). For some local governments, even though they were not so confident about AI prospects, they still took AI initiatives out of the concern that they would lag behind others if they did nothing (GV13).

AI companies also strived for legitimacy. When asked about AI's negative impacts, most industrial interviewees advocated that AI per se was neither good nor evil, but how it is used mattered (ET05; ET18; ET30; ET35; ET62; ET63). A manager from a surveillance camera company argued the following:

> Surveillance technology is like a knife. You can't say having a knife is only for murder. As a technology provider, we have no say in how the technology should be used, and we have nothing to do with the legitimacy involved in applications. (ET18)

Many AI players, especially large digital platforms, tried to promote a positive image of AI in social governance. For instance, face-recognition companies often highlight the use of AI in finding missing persons, especially children and the elderly (ET01; ET37; WT63). AI firms also sought to emphasize a collaborative human–AI relation and AI's long-term impacts on creating new jobs (ET05; ET62). Facing such an emerging but controversial technology, most industrial actors advocated 'let the bullet fly' (ET62) rather than early regulations.

Besides, large digital platforms actively established public policy research institutes and hired social scientists, lawyers and former government officials, aiming to study the frontier of the industry and influence public policies (ET26; ET46; ET48; ET52). Leveraging their rich real-time data, these digital platforms usually collaborated with influential universities to publish research reports regularly on controversial topics such as employment, data, privacy and ethics, which influenced public opinions about AI. A public relations manager from an AI firm stated: 'On the frontier social issues, we collaborate with universities to correct some wrong public ideas and to guarantee our products can be accepted on the market' (ET52). AI companies also actively participated in forming national AI regulations. For example, some leading AI entrepreneurs were on the board of MOST's National AI Governance Committee and contributed to the release of China's AI governance principles in 2019.

THE FORMATION OF THE FOUNDATION-LEVEL RESOURCE

Data: spatially sticky

At the foundational level of the AI innovation system, data are a spatially sticky resource. The availability of data is strongly conditioned by a country's legal and socio-economic context. Although China has a big data-labelling cluster providing services for both domestic and foreign AI companies, labelled data are only a small part of China's data advantage, which mainly lies in China's huge population and pervasive use of internet applications. As the payoff of rapid internet economic development, China has become the 'OPEC in data',[1] accounting for 20% of the world's internet users (Ding, 2018). Moreover, China's lax formal and informal institutions on data protection facilitated a rather loose regime on data use. It was not until 2020 when China realized its first comprehensive draft law on personal information protection. Unlike in Western cultures where privacy is usually seen as an individual right, perceptions of privacy in Chinese society are more oriented by the value of collectivism, community and 'saving face' (Li et al., 2021). Chinese society had relatively fewer concerns about personal data protection and was more willing to embrace the novelties, securities, efficiencies and conveniences brought by new technologies at the cost of a certain level of privacy (Arenal et al., 2020). These contextualized institutions allowed low-cost accumulations of large – though also often low-quality – data for both AI algorithm training and marketing. A director of an multinational corporation's (MNC) research branch stated: 'such as internet plus, big data, China has no strict legislation, so there is a room for development, and China can cross the river by feeling the stones' (ET06).

Nonetheless, this lax data regulation was under increasingly heated debate. International data regulations were also pushing China's AI industry to improve its data protection standards. Among them, the European Union's (EU) General Data Protection Regulation (GDPR) was most influential. Several Chinese AI firms have invested heavily to upgrade their privacy standards to expand their international businesses (ET29; RI38; ET44; ET47; ET48; ET60; ET65).

Under such a context, the AI industry endeavoured to secure as much data as possible, on the one hand, and influence the data regime when they were still in flux, on the other. AI firms and digital platforms were expanding to downstream applications to acquire data, even if no profits were promised in the short run. For example, Tencent, a digital giant focusing on social networks and entertainment, established an autonomous driving department in 2016. A technology manager explained the rationale:

> On the one hand, autonomous driving could bring an industrial transformation where cars are at the centre for future mobility and entertainment. On the other hand, it is about the volume of data related to autonomous driving, which could be very important to our cloud business.
>
> (ET53)

Some AI companies provided free equipment to users on the condition that they can obtain access to users' data (ET54). Moreover, there were increasing calls from the industry asking governments to open access to more public data (ET23; ET25; ET47; ET48; GV50; ET63). Many local governments have initiated digital government projects and established specialized bureaus for data management across government agencies (GV50; GV51).

Benefiting from incumbent loose data regulations, most AI firms advocated continuing the existing regime with certain levels of improvement. A digital platform manager stated: 'I think if we consider this (stricter data protection) too early, it might constrain our current development strategies' (ET15). The GDPR was widely argued to put the industry at a competitive disadvantage, and the dominant discourse among the industry was that China needed to improve its data protection but not to the level of GDPR (ET18; RI38; ET48; ET60; ET63). There were also firms complaining that current ambiguous data regulations created a long-term risk for China's AI industry and thus called for clear regulations on data ownership and use (ET48; IA49; ET65). In April 2020, China's State Council issued an opinion on the reform of the factor market and listed data as the fifth production factor, parallel to the conventional factors of land, labour, capital and technology, urging open access to more government data, improved data value and quality, and strengthened data protection.

DISCUSSION

From the GIS perspective, the AI industry is a market-anchored GIS. In general, its knowledge and financial investment are footloose at the global level while the market, legitimacy and data are much more place sticky. These resources are closely intertwined and reinforce each other in China's AI innovation system. From an evolutionary view, China's AI industry inherits most of these resources, especially the market, legitimacy and data, from its internet economy. China's huge market and loose regime drove the internet economy and gave rise to various internet applications and digital platforms. The development of the mobile internet in the late 2000s greatly facilitated the diffusion of many innovations, such as food delivery, e-payment, bike-sharing and online car-hailing, which brought not only massive data but also more legitimacy for new technologies. When AI knowledge became mature in the early 2010s, entrepreneurs began to leverage China's rich data to improve AI technologies and develop new business models. After 2016, the victory of AlphaGo and the central government's AI strategy provided further legitimacy, leading to more government support, more AI investments and a larger AI market. Furthermore, digital platforms and AI unicorns expanded the AI market to various scenarios and developed institutional power to strengthen the legitimacy of AI development in China.

Previous research has equally emphasized the role of each system resource in system formation, but it has insufficiently explained why new path creations only occur in certain places (Binz et al., 2016). Our results show that some unique sticky resources should be presented in a place before footloose resources could be attracted and anchored to the local context. China's huge market and rich data are the key assets that draw other resources to its AI innovation system. These resources were not born there but are an outcome of the interaction between multi-scalar institutions and actor strategies (Table 1).

As the emergence of the AI industry is relatively new to the world, 'one can expect windows of opportunity to exist in regions where the regime is less dominant and only weakly institutionalized or hybridized' (Boschma et al., 2017, p. 38). China's less institutionalized regime plays a critical role in gaining first-mover advantages in AI development. As Table 1 shows, the formation of market, legitimacy and data in China are closely associated with its low entry barrier, high social acceptance of innovations, lower privacy standards and lax data regulations. In this sense, the catch-up of China's AI industry is not much different from that of many conventional industries (e.g., automobiles), which rely on extra-regional knowledge but benefit mainly from China's demographic dividends and institutional dividends (e.g., lower environmental standards). Whereas some Western countries have implemented strict data regulations and banned some AI technologies, China advances AI development with a trial-and-error approach (Arenal et al., 2020). This philosophy of 'crossing the river by feeling the stones' allows more room for AI entrepreneurial experiments and policy

Table 1. System resources, institutions, and actor strategies in China's artificial intelligence (AI) industry.

Level	Resources	Spatial characteristics	Multi-scalar institutions	Actors' strategies
Function	Knowledge	Footloose	Global open-source communities; international academic networks	Combining external knowledge with local data and applications; attracting oversea talents; oversea acquisitions; returnee entrepreneurship; international collaborations
	Investment	Footloose	Global investment rationale	Investment from international/domestic investors; digital giants invest to expand their ecosystems; government funding
	Market	Spatially sticky	Huge population; high AI demand; low entry barriers; '*Guanxi*'	Governments create niche markets and support applications; digital platforms and AI firms' 'AI+'; '+AI' by conventional sectors; entering international markets
	Legitimacy	Spatially sticky	Philosophy of 'development first'; high acceptance of innovations; trust in public organizations	Government's planning and supports; AI firms promote positive images of AI; digital giants influence AI institutions
Foundation	Data	Spatially sticky	Booming internet economy; loose data regulation; community-oriented privacy	Accumulating data by penetrating to applications; calling for open data; lobbying for moderate data regulations

experiments but may also risk ending up following the development pathway of 'pollution first, clean up later'.

Our case has also highlighted the role of actor strategies in both coupling system resources and shaping the institutional environment. China's national innovation system is usually described as a 'statist' triple helix (Ranga & Etzkowitz, 2013), where the government dominates the direction of academic research and industry development. This triple helix is changing in the AI innovation system, which is mainly market driven and led by digital platforms and AI entrepreneurs (Yu et al., 2021). Scientist entrepreneurs not only linked global knowledge with local markets but also provided certain legitimacy and positive signal effects to investors. Digital giants and MNCs anchored global resources, contributing to the local cluster through the 'global pipeline and local buzz' model (Bathelt et al., 2004). In addition, the industry actively strived to shape the loose institutional regime before it was fully established. They advocated positive images of AI and collaborated with universities to influence public opinions and policymaking, acting in the role of institutional entrepreneurship. Nevertheless, the government also played an important role as a supporter, an enabler, a regulator and a customer. The central government and local governments have considerably contributed to the AI innovation system in guide of search (e.g., strategic planning), market formation (e.g., procurement), investment mobilization (e.g., government funding) and legitimization. More importantly, the government facilitated the formation of the foundational resource by, for example, providing lax regulations, opening access to government data and listing data as a new production factor.

Finally, this study also implies the role of data in strengthening the power of large digital platforms in data-driven innovation systems. In the AI era, data are critical not only for knowledge development but also for market formation and public policymaking (Yu et al., 2021). Owning critical resources could enable certain actors to become prime movers and develop structural power to direct meso-level system changes (Markard & Truffer, 2008). This is particularly true for data-driven innovations because the network effects of data usually result in a few giant digital platforms controlling most of the valuable data. Those who can control data could gain not only tremendous commercial value but also discursive and institutional power to shape the innovation system. Digital giants such as BAT played a central role as prime movers in coupling the system resources for China's AI industry. Moreover, they considerably affected how AI was discussed by the public and policymakers and hence influenced the formal and informal institutions around the emerging AI industry.

CONCLUSIONS

To understand the geography of emerging data-driven industries, this paper develops a modified GIS approach and investigates how the AI industry emerges in China. Data are the foundational resource in data-driven innovations and significantly influence the formation of function-level resources. The AI industry is a market-anchored GIS in which knowledge and financial investment are footloose while market, legitimacy and data are highly contingent on local contexts. China's loose institutional regime significantly facilitates the formation of market, data and legitimacy. AI entrepreneurs and digital platforms couple these resources into China's AI innovation system and also act as institutional entrepreneurship to shape the changing institutional environment.

There are two contributions of this paper to the literature. First, building upon the recently developed GIS framework, it proposes a conceptual approach to depict the rise of an emerging industry through the interplay between its GIS characteristics, multi-scalar interactions and actor strategies. This conceptual approach acknowledges industry-specific resource mobilities and points to the key role of structure-agency interaction in shaping emerging industries where institutions are usually in flux. Second, responding to the call for novel approaches to capture innovation system dynamics in a digitalized world, this paper differentiates two levels of system resources in data-driven innovation systems and conceptualizes data as the foundation-level system resource. Data are not merely a new production factor, they are also highly associated with the formation of knowledge, investment, market and legitimacy. Therefore, those who control a large amount of valuable data could develop structural power to direct the evolution of data-driven industries. Nevertheless, a deeper understanding of the process of data-shaping power structures could be further studied in future research.

ACKNOWLEDGEMENT

The authors thank all the interviewees who participated in this study and shared their thoughts.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

FUNDING

This research was supported by the National Key R&D Program of China [grant number 2020AAA0105300]; the National Natural Science Foundation of China [grant numbers 71810107004 and 71774097]; and the Tsinghua University Independent Research Program [grant number 2019THZW].

NOTE

1. OPEC = Organization of the Petroleum Exporting Countries.

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REFERENCES

Abraham, R., Schneider, J., & vom Brocke, J. (2019). Data governance: A conceptual framework, structured review, and research agenda. *International Journal of Information Management*, *49*, 424–438. https://doi.org/10.1016/j.ijinfomgt.2019.07.008

Agrawal, A., Gans, J., & Goldfarb, A. (2019). Economic policy for artificial intelligence. *Innovation Policy and the Economy*, *19*(1), 139–159. https://doi.org/10.1086/699935

Arenal, A., Armua, C., Feijoo, C., Ramos, S., Xu, Z., & Moreno, A. (2020). Innovation ecosystems theory revisited: The case of artificial intelligence in China. *Telecommunications Policy*, *44*(6), 101960. https://doi.org/10.1016/j.telpol.2020.101960

Bathelt, H., Malmberg, A., & Maskell, P. (2004). Clusters and knowledge: Local buzz, global pipelines and the process of knowledge creation. *Progress in Human Geography*, *28*(1), 31–56. https://doi.org/10.1191/0309132504ph469oa

Battilana, J., Leca, B., & Boxenbaum, E. (2009). How actors change institutions: Towards a theory of institutional entrepreneurship. *Academy of Management Annals*, *3*(1), 65–107. https://doi.org/10.5465/19416520903053598

Benaich, N., & Hogarth, I. (2020). *State of AI report*. https://www.stateof.ai/

Bergek, A., Jacobsson, S., Carlsson, B., Lindmark, S., & Rickne, A. (2008). Analyzing the functional dynamics of technological innovation systems: A scheme of analysis. *Research Policy*, *37*(3), 407–429. https://doi.org/10.1016/j.respol.2007.12.003

Binz, C., Gosens, J., Yap, X., & Yu, Z. (2020). Catch-up dynamics in early industry lifecycle stages – A typology and comparative case studies in four clean-tech industries. *Industrial and Corporate Change*, *29*(5), 1257–1275. https://doi.org/10.1093/icc/dtaa020

Binz, C., & Truffer, B. (2017). Global innovation systems – A conceptual framework for innovation dynamics in transnational contexts. *Research Policy*, *46*(7), 1284–1298. https://doi.org/10.1016/j.respol.2017.05.012

Binz, C., Truffer, B., & Coenen, L. (2016). Path creation as a process of resource alignment and anchoring: Industry formation for on-site water recycling in Beijing. *Economic Geography*, *92*(2), 172–200. https://doi.org/10.1080/00130095.2015.1103177

Boggs, J. S., & Rantisi, N. M. (2003). The 'relational turn' in economic geography. *Journal of Economic Geography*, *3*(2), 109–116. https://doi.org/10.1093/jeg/3.2.109

Boschma, R., Coenen, L., Frenken, K., & Truffer, B. (2017). Towards a theory of regional diversification: Combining insights from evolutionary economic geography and transition studies. *Regional Studies*, *51*(1), 31–45. https://doi.org/10.1080/00343404.2016.1258460

Boschma, R., & Frenken, K. (2011). The emerging empirics of evolutionary economic geography. *Journal of Economic Geography*, *11*(2), 295–307. https://doi.org/10.1093/jeg/lbq053

Bresciani, S., Ciampi, F., Meli, F., & Ferraris, A. (2021). Using big data for co-innovation processes: Mapping the field of data-driven innovation, proposing theoretical developments and providing a research agenda. *International Journal of Information Management*, *102347*, 1–15. https://doi.org/10.1016/j.ijinfomgt.2021.102347

Butcher, J., & Beridze, I. (2019). What is the state of artificial intelligence governance globally? *The RUSI Journal*, *164*(5–6), 88–96. https://doi.org/10.1080/03071847.2019.1694260

Curry, E. (2016). The big data value chain: Definitions, concepts, and theoretical approaches. In J. Cavanillas, E. Curry & W. Wahlster (Eds.), *New horizons for a data-driven economy* (pp. 29–37). Springer.

Ding, J. (2018). *Deciphering China's AI dream: The context, components, capabilities, and consequences of China's strategy to lead the world in AI*. Faculty of Humanity Institute, University of Oxford.

Gong, H., & Hassink, R. (2019). Developing the Shanghai online games industry: A multi-scalar institutional perspective. *Growth and Change*, *50*(3), 1006–1025. https://doi.org/10.1111/grow.12306

Grillitsch, M. (2019). Following or breaking regional development paths: On the role and capability of the innovative entrepreneur. *Regional Studies*, *53*(5), 681–691. https://doi.org/10.1080/00343404.2018.1463436

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, *61*(4), 5–14. https://doi.org/10.1177/0008125619864925

Hartmann, P., & Henkel, J. (2018). Really the new oil? A resource-based perspective on data-driven innovation. *Academy of Management Global Proceedings*, *Surrey*, 142.

Hekkert, M. P., Suurs, R. A. A., Negro, S. O., Kuhlmann, S., & Smits, R. E. H. M. (2007). Functions of innovation systems: A new approach for analysing technological change. *Technological Forecasting and Social Change*, *74*(4), 413–432. https://doi.org/10.1016/j.techfore.2006.03.002

Jonas, A. E. (2012). Region and place: Regionalism in question. *Progress in Human Geography*, *36*(2), 263–272. https://doi.org/10.1177/0309132510394118

Karnøe, P., & Garud, R. (2012). Path creation: Co-creation of heterogeneous resources in the emergence of the Danish wind turbine cluster. *European Planning Studies*, *20*(5), 733–752. https://doi.org/10.1080/09654313.2012.667923

Kenney, M., & Zysman, J. (2016). The rise of the platform economy. *Issues in Science and Technology*, *3*, 61–69.

Kern, F. (2015). Engaging with the politics, agency and structures in the technological innovation systems approach. *Environmental Innovation and Societal Transitions*, *16*, 67–69. https://doi.org/10.1016/j.eist.2015.07.001

Klingenberg, C. O., Borges, M. A. V., & Antunes, J. A. V., Jr. (2019). Industry 4.0 as a data-driven paradigm: A systematic literature review on technologies. *Journal of Manufacturing Technology Management*, *32*(3), 570–592. https://doi.org/10.1108/JMTM-09-2018-0325

Li, T., Bronfman, J., & Zhou, Z. (Forthcoming 2021). Saving face: Unfolding the screen of Chinese privacy law (August 2017). *Journal of Law, Information, and Science*. https://ssrn.com/abstract=2826087

Markard, J., & Truffer, B. (2008). Actor-oriented analysis of innovation systems: Exploring micro–meso level linkages in the case of stationary fuel cells. *Technology Analysis & Strategic Management*, *20*(4), 443–464. https://doi.org/10.1080/09537320802141429

Martin, R. (2000). Institutional approaches in economic geography. In E. Sheppard & T. J. Barnes (Eds.), *A companion to economic geography* (pp. 77–94). Blackwell.

Parkins, D. (2017). The world's most valuable resource is no longer oil, but data. *The Economist*. https://www.economist.com/leaders/2017/05/06/the-worlds-most-valuable-resource-is-no-longer-oil-but-data

Porter, M. E. (2008). *Competitive strategy: Techniques for analyzing industries and competitors*. Simon & Schuster.

Ranga, M., & Etzkowitz, H. (2013). Triple helix systems: An analytical framework for innovation policy and practice in the knowledge society. *Industry and Higher Education*, *27*(4), 237–262. https://doi.org/10.5367/ihe.2013.0165

Roberts, H., Cowls, J., Morley, J., Taddeo, M., Wang, V., & Floridi, L. (2020). The Chinese approach to artificial intelligence: An analysis of policy, ethics, and regulation. *AI & Society*, 3. https://doi.org/10.1007/s00146-020-00992-2

Saura, J. R., Ribeiro-Soriano, D., & Palacios-Marqués, D. (2021). From user-generated data to data-driven innovation: A research agenda to understand user privacy in digital markets. *International Journal of Information Management*, *102331*, 1–13. https://doi.org/10.1016/j.ijinfomgt.2021.102331

Trabucchi, D., & Buganza, T. (2019). Data-driven innovation: Switching the perspective on big data. *European Journal of Innovation Management*, *22*(1), 23–40. https://doi.org/10.1108/EJIM-01-2018-0017

Valle-Cruz, D., Criado, J. I., Almazan, R. S., & Ruvalcaba-Gómez, E. A. (2020). Assessing the public policy-cycle framework in the age of artificial intelligence: From agenda-setting to policy evaluation. *Government Information Quarterly*, *37*(4), 101509. https://doi.org/10.1016/j.giq.2020.101509

Weber, K., & Truffer, B. (2017). Moving innovation systems research to the next level: Towards an integrative agenda. *Oxford Review of Economic Policy*, *33*(1), 101–121. https://doi.org/10.1093/oxrep/grx002

Weber, S. (2017). Data, development, and growth. *Business and Politics*, *19*(3), 397–423. https://doi.org/10.1017/bap.2017.3

Xue, L., Liang, Z., Yu, Z., Huang, C., Wang, L., Zhi, Q., Zhu, J., He, J., Xie, S., Guo, Y., Su, J., Wang, Y., Li, D., & Wang, X. (2018). *China artificial intelligence development report 2018*. China Institute of Science and Technology Policy at Tsinghua University.

Yap, X., & Truffer, B. (2019). Shaping selection environments for industrial catch-up and sustainability transitions: A systemic perspective on endogenizing windows of opportunity. *Research Policy*, *48*(4), 1030–1047. https://doi.org/10.1016/j.respol.2018.10.002

Yu, T. F. (2001). An entrepreneurial perspective of institutional change. *Constitutional Political Economy*, *12*(3), 217–236. https://doi.org/10.1023/A:1011607927754

Yu, Z., & Gibbs, D. (2020). Unravelling the role of Green entrepreneurs in urban sustainability transitions: A case study of China's solar city. *Urban Studies*, *57*(4), 2901–2917. https://doi.org/10.1177/0042098019888144

Yu, Z., Liang, Z., & Wu, P. (2021). How data shape actor relations in artificial intelligence innovation systems: An empirical observation from China. *Industrial and Corporate Change*, *30*(1), 251–267. https://doi.org/10.1093/icc/dtaa063

Zhang, W., & White, S. (2016). Overcoming the liability of newness: Entrepreneurial action and the emergence of China's private solar photovoltaic firms. *Research Policy*, *45*(3), 604–617. https://doi.org/10.1016/j.respol.2015.11.005