Public Procurement of Innovation and Regional Technological Diversification: The Role of Local and Non-local Sourcing in China

Yuqi Ma, Zhaoyingzi Dong, Pierre-Alexandre Balland & Hantian Sheng

Papers in Evolutionary Economic Geography

26.09

Utrecht University Human Geography and Planning

Public Procurement of Innovation and Regional Technological Diversification: The Role of Local and Non-local Sourcing in China

Yuqi Ma
School of Public Affairs, Zhejiang University, China

Zhaoyingzi Dong
School of Public Affairs, Zhejiang University, China

Pierre-Alexandre Balland
Growth Lab, Harvard Kennedy School, Harvard University, USA
Centre for European Policy Studies, Belgium

Hantian Sheng
School of Public Affairs, Zhejiang University, China

Corresponding author: Zhaoyingzi Dong, dongzhaoyingzi@zju.edu.cn

Public Procurement of Innovation and Regional Technological Diversification: The Role of Local and Non-local Sourcing in China

Abstract: Public procurement of innovation (PPI) is widely regarded as a powerful demand-side policy instrument to stimulate innovation, but its role in shaping regional technological diversification remains unclear. Drawing on evolutionary economic geography, this study examines how PPI affects technological diversification under different spatial sourcing strategies. Using 2.24 million procurement contracts and 2.41 million patents from China (2016-2021), we find that PPI facilitates path-breaking diversification, but mainly through non-local procurement. Compared with local procurement, non-local procurement is more conducive to path-breaking diversification in purchasing regions, while its benefits do not spill over symmetrically to supplying regions. By reconceptualizing PPI as a spatially embedded and relational mechanism, this study extends evolutionary accounts of regional diversification beyond a purely territorial lens and highlights how the spatial organization of public demand shapes uneven opportunities for regional technological development.

Keywords: Public procurement of innovation; Technological diversification; Path-breaking innovation; Non-local procurement; Evolutionary economic geography

1 Introduction

Technological diversification is widely regarded as a key driver of regional innovation quality and long-term competitiveness. However, a large body of work in evolutionary economic geography shows that this process is highly path-dependent and unevenly distributed across space (Balland & Rigby, 2017; Dong et al., 2022, 2025; Turkina et al., 2025). As innovation activities tend to build cumulatively on existing knowledge bases and capabilities, regions are more likely to diversify into technological domains that are related to their existing specializations, thereby limiting path-breaking innovation (Chen et al., 2025). To overcome these path-dependent constraints, scholars and policymakers have increasingly emphasized the role of policy interventions in introducing external knowledge and capabilities needed in the path-breaking diversification (Radicic, 2019; Eckersley et al., 2023; Zhu et al., 2026).

Among these interventions, public procurement of innovation (PPI, hereafter) has emerged as a demand-side policy instrument with the potential to stimulate innovation while advancing broader regional development objectives (Crespi & Guarascio, 2019; Day & Merkert, 2023). Originally conceptualized by Edquist et al. (2000), PPI refers to the procurement of goods, services, or solutions that require new technologies or innovation to meet public needs. Literature has acknowledged that PPI can create public demand, reduce market uncertainty, and facilitate the commercialization of emerging technologies (Edquist & Zabala-Iturriagagoitia, 2020; Uyarra et al., 2020; Castelnovo et al., 2023). However, its influence on regional technological diversification remains insufficiently understood. In particular, it remains unclear whether PPI facilitates path-breaking diversification by supporting regions move beyond existing technological trajectories, or instead reinforces path-dependent diversification.

This question is especially important because the effects of PPI are unlikely to be uniform across regions and procurement arrangements. Existing studies mostly treat PPI as a local, place-based policy tool and adopt a purchaser-centric perspective, emphasizing how public demand supports local firms and strengthens regional innovation systems (Uyarra et al., 2020; Day & Merkert, 2023). Yet procurement activities are not always confined within local boundaries. Though favoring local suppliers has long been a common practice in PPI (Herz & Varela-Irimia, 2020; Lu & Wang, 2022), procurement often extends beyond local boundaries when required knowledge and capabilities are not locally available. Such non-local procurement can disrupt the insularity of local innovation systems, expand cross-regional knowledge flows, and introduce more heterogeneous technological inputs (Uyarra et al., 2014; Van Winden & Carvalho, 2019). Moreover, purchasing regions and supplying regions may be affected differently in non-local procurement. However, existing studies make little distinction between local and non-local procurement, nor do they examine how non-local procurement affects purchasing and supplying regions differently.

Within this context, this study examines the impact of PPI on technological diversification and investigates whether this impact varies across different spatial sourcing strategies. Drawing on a novel city-technology-year panel dataset by combining more than 2.24 million public procurement contracts with 2.41 million patent records in China from 2016 to 2021, we identify PPI contracts through a text-based classification strategy based on technology-intensive and innovation-related keywords, and further distinguish between local and non-local PPI according to the locations of purchasers and suppliers. The empirical results show that PPI encourages cities to expand into relatively less related technological domains, thereby fostering path-breaking technological diversification. However, its effects depend critically on spatial sourcing strategies. Compared with local procurement, non-local procurement is more conducive to path-breaking diversification. However, while non-local procurement promotes path-breaking diversification for purchasing locations, its positive effects do not symmetrically extend to supplying regions and cannot stimulate technological diversification there.

By doing so, this study extends the existing research in three key aspects. First, it integrates insights from evolutionary economic geography and public procurement scholarship, by examining the effects of PPI from the perspective of regional technological diversification Evolutionary economic geography has predominantly analyzed how regions evolve through technological diversification processes from a supply-side perspective, while public procurement research has primarily examined PPI as a place-based policy instrument that stimulates local innovation outcomes (Radicic, 2019; Uyarra et al., 2020; Stojčić et al., 2020; Castelnovo et al., 2023). Although recent studies have begun to examine how demand-side forces affect tinnovation outputs or entry into new technological domains (Zhang and He, 2026; Sunley et al., 2020; Mu et al., 2026), less attention has been paid to how PPI contributes to technological diversification through its interaction with regions' existing technological structures. By conceptualizing PPI as a demand-side policy tool and distinguishing between local and non-local procurement sources, this study advances a more nuanced account of how different spatial sourcing strategies differentially shape regional technological diversification trajectories, thereby contributing the emerging literature on demand-side sources of regional evolution.

Second, this study advances the literature by reconceptualizing PPI as a spatially embedded and relational mechanism rather than a purely place-based policy tool. While prior studies have primarily examined PPI as a place-based instrument that stimulates local innovation, research on place-based policy emphasizes that place-based interventions may generate uneven spatial consequences by redistributing opportunities, resources, and market access across locations (Barca et al., 2012; Koster et al., 2019). Building on this perspective, this study shows that the effects of PPI depend on how procurement demand is spatially sourced. Non-local procurement enables purchasing regions to access external technological capabilities and supports path-breaking diversification, whereas local procurement is more closely tied to existing regional capabilities and supplier relationships. Moreover, the benefits of non-local procurement do not spill over to supplying regions in the form of broader technological diversification. This divergence highlights the spatial asymmetry of purchaser-supplier relationships, and underscores how the spatial organization of public demand can unevenly redistribute opportunities for technological upgrading across regions.

Third, the study provides large-scale empirical evidence on how PPI shapes the direction of regional technological diversification. Prior research has established the theoretical rationale for using PPI to foster innovation, but empirical studies have often relied on qualitative evidence, firm-level innovation responses, or aggregate innovation indicators such as patent counts and R&D expenditure. By combining large scale procurement records with patent data, this paper links PPI to specific patterns of technological entry. Empirically, the study therefore provides novel large-scale evidence on how different spatial sourcing strategies of PPI shape regional technological trajectories and generate uneven consequences across purchasing and supplying regions.

The remainder of this paper is structured as follows. Section 2 elaborates on the theoretical background, while Section3 outlines the hypothesis development underpinning this research. Section 4 outlines the methodology and data utilized for the empirical analysis. Section 5 presents the empirical results, discussing the findings and their implications. Finally, Section 6 offers concluding remarks and avenues for future research.

2 Literature Review

2.1 Regional Technological Diversification

In evolutionary economic geography (EEG) literature, technological diversification is closely linked to innovation, as it captures the process through which regions expand into new technological domains and reshape regional underlying knowledge structures (Breschi et al., 2003; Boschma et al., 2015; Balland et al., 2018; Lo Conte et al., 2025; Wei et al., 2025). This process is not random, but is strongly conditioned by relatedness, which reflects similarities and differences in the capabilities required to develop different technologies (Breschi et al., 2003; Balland et al., 2018). Because regions accumulate capabilities through their existing specializations, they are more likely to diversify into related technological domains that are closely related to their existing activities (Boschma, 2016; Quatraro & Scandura, 2024). Such related diversification enables regions to exploit complementarities among technologies, reduce uncertainty, and support incremental innovation along established technological trajectories (Zhu et al., 2017; Balland & Boschma, 2021).

However, regional technological upgrading also depends on the capacity to move beyond related diversification. Less related diversification occurs when regions expand into technological domains that share fewer cognitive, technological, or capability overlaps with their existing knowledge base, requiring the recombination of knowledge drawn from more distant and heterogeneous fields (Dong et al., 2022, 2025; Lo Conte et al., 2025). It therefore involves higher uncertainty, greater costs, and more substantial learning efforts (Neffke et al., 2011; Boschma, 2016). Yet precisely because it allows regions to deviate from established trajectories, less related diversification is widely regarded as a key source of path-breaking innovation.

Path-breaking diversification enables regions to explore new technological directions rather than merely extending their inherited knowledge base (Markard et al., 2012; Nilsson et al., 2025). Prior studies have emphasized the role of external knowledge, interregional linkages, and policy interventions in enabling regions to pursue path-breaking diversification (Dong et al., 2025; Lo Conte et al., 2025; Zhu et al., 2026). Therefore, regional technological diversification should not be understood solely as an outcome of local capability accumulation. It is also shaped by how regions are connected to external knowledge, markets, and policy-induced demand.

This observation resonates with recent debates in evolutionary economic geography that call for greater attention to demand-side forces in regional diversification (Sunley et al., 2020). Mackinnon et al. (2019) conceptualize a demand-side driven framework of regional path creation, while Martin et al. (2019) further disentangle the roles that demand may play in regional industrial diversification. To be more specific, Martin and Martin (2023) propose that demand may take multiple forms, including general consumption patterns, co-development between users and producers, public procurements and values among consumers. Unlike the supply-side perspective, the demand-side perspective places greater emphasis on how public or market demand influence the direction of regional evolve by shaping the linkages between inputs and outputs, industries and skills, and production and application contexts (Zhang et al., 2024; Ao et al., 2026). In the context of technological diversification, this perspective is particularly relevant for China, where local governments play an important role in shaping demand-side regional diversification through place-based policy interventions (He & Zhang, 2021).

2.2 The Role of Public Procurement of Innovation in Regional Technological Diversification

Public procurement represents one of the most important demand-side policy instruments through which local governments can shape innovation and technological evolution. By consolidating markets, reducing uncertainty, and incentivizing suppliers todiversification develop upgraded goods and services, public procurement can influence not only the volume of innovation but also its direction (Uyarra et al., 2020; Castelnovo et al., 2023). Recently, some empirical studies have begun to examine the impact of public procurement on regional diversification. For instance, Mu et al. (2026) argue that public procurement acts as a key driver for the development of China's photovoltaic industry. Zhao et al. (2025) propose that public procurement induced by industry policies promotes private adoption of new energy vehicles. Furthermore, Li et al. (2026) add that public procurement, as a prominent way of policy intervention, compensates for the lack of local technology application industries, contributing to the cross-regional and cross-industry spillovers of industrial robot technologies.

Compared to regular public procurement (RPP), public procurement of innovation (PPI), which involves purchasing previously non-existent products or processes to meet public needs (Edquist et al., 2020; Caravella & Crespi, 2021), is uniquely positioned to drive radical innovation (Castelnovo et al., 2023). Through procuring innovative goods and services, PPI can send clear market signals to potential private suppliers concerned about costs and risks (Radicic, 2019; Uyarra et al., 2020). Serving as an 'experimental customer', governments can absorb risks tied to novel, unproven technologies (Dai et al., 2021), and help suppliers recover sunk costs from innovation investments (Stojčić et al., 2020). Thus, PPI justifies suppliers' innovative endeavors though alleviating financial constraints and enabling cost reductions (Crespi & Guarascio, 2019; Castelnovo et al., 2023; Day & Merkert, 2023). Georghiou et al. (2014) found that nearly half of firms awarded PPI contracts increased their R&D expenditure in response. Despite this recognition, how PPI influences the dynamic process of technology diversification, particularly its role in breaking path dependence, remains under-explored.

Understanding this role requires attention not only to whether procurement is innovation-oriented, but also to how procurement demand is spatially sourced. PPI is increasingly framed as a place-based policy tool to support local firms and foster local innovation systems (Uyarra et al., 2020; Day & Merkert, 2023). As major (often the largest) purchasers, governments leverage their significant purchasing power through local procurement, prioritizing local suppliers to enhance urban competitiveness and achieve goals beyond cost efficiency (Herz & Varela-Irimia, 2020; Uyarra et al., 2020; Eckersley et al., 2023; Liu, et al., 2026). Nevertheless, adopting local procurement strategy potentially excludes innovative solutions and their positive effects. First, this approach restricts the pool of potential suppliers, thereby risking market distortion (Eckersley et al., 2023). Local suppliers may secure procurement contracts through non-competitive channels (Lu & Wang, 2022), which further fosters product replication, irrational investment, and corruption risks (Georghiou et al., 2014; Holma et al., 2022). Moreover, preferences for local suppliers may reinforce organizational inertia, thus local suppliers tend to grow less responsive to external competition and less capable of achieving innovation breakthroughs (Kutlina-Dimitrova & Lakatos, 2016). When local suppliers underperform, it may also erode economies of scale and impeding the development of comparative advantage (Lerusse & Van de Walle, 2022).

By contrast, non-local procurement means the required information and knowledge are not locally available but require engaging with geographically dispersed, non-local suppliers. Securing non-local demands is not a simple affair, as competition within regional procurement markets is anticipated to be highly intense (Day & Merkert, 2023). Anderson et al. (2012) argue that competitive procurement markets are critical to achieve value through three mechanisms: expanding market access to reduce collusion, strengthening incentives for suppliers to improve efficiency, and significantly boosting inducements for innovation. Existing research has examined how non-local procurement links cities' existing innovation capabilities with external knowledge and expands their technological repertoires (Mason & Brown, 2013).

However, this literature has largely focused on purchasing regions, treating suppliers mainly as conduits of external knowledge rather than as regions embedded in their own local innovation systems. Consequently, empirical evidence on the impacts of non-local procurement on supplying regions remains scarce.

3 Hypothesis Development

PPI, as a demand-side policy instrument, is characterized by its explicit focus on driving innovation. Explicitly targeting innovation, PPI enables governments in their role as purchasers to directly incentive suppliers to develop novel solutions (Krieger et al., 2024; Similä & Mwesiumo, 2024). Existing empirical literature has extensively confirmed PPI' s positive effects in driving innovation through multiple channels, including guaranteeing market scale, absorbing risks associated with new technologies, and co-creating solutions through purchaser-supplier interactions (Crespi & Guarascio, 2019; Castelnovo et al., 2023; Krieger et al., 2024).

From an evolutionary economic geography perspective, the innovation effects of PPI depend not only on policy instruments but also on how their interaction with regions' existing knowledge structures. Technological diversification is shaped by path dependence, as regions are generally more likely to enter domains that are related to their accumulated capabilities. PPI may help loosen such constraints by creating demand for solutions that are not yet available on the market. By reducing uncertainty and providing an initial market for exploratory innovation, PPI can encourage firms and regions to experiment beyond established technological trajectories (Edquist & Zabala-Iturriagagoitia, 2020; Uyarra et al., 2020; Patrucco et al., 2024). Such demand-pull effects may incentivize experimentation beyond established technological trajectories, supporting the development of technologies that are less closely related to regions' existing knowledge bases.

Accordingly, we propose the first hypothesis:

H1: *Public procurement of innovation (PPI) facilitates path-breaking technological diversification.*

However, as mentioned above, the effects of PPI are not uniform. They may depend on how procurement demand is spatially sourced and how purchaser-supplier relationships are organized across regions.

In the case of local PPI, the effect can be twofold. On the one hand, local PPI may provide additional financial resources and stable demand for local firms, thereby reducing the uncertainty and costs associated with exploratory innovation. Such demand-side support can help firms undertake more risky technological experimentation and potentially facilitate path-breaking diversification, especially when firms face financial constraints or when emerging technologies lack mature markets. On the other hand, local procurement tends to embed public demand within the existing regional innovation system and direct toward local incumbent firms, procurement may reinforce path dependence by repeatedly favoring suppliers with proven capabilities (Holma et al., 2022; Zabala-Iturriagagoitia, 2022). By limiting the pool of potential suppliers, particularly non-local suppliers, local firms may secure contracts through less competitive channels, reinforcing organizational inertia and reducing their responsiveness to external technological dynamics (Uyarra & Flanagan, 2010; Kutlina-Dimitrova & Lakatos, 2016). Furthermore, local procurement may heighten the risk of collusion or political interference in innovation activities, thereby constraining supplier autonomy and discouraging creative experimentation (Georghiou et al., 2014; Holma et al., 2022).

By contrast, non-local procurement extends public demand beyond the purchasing region and connects local governments with geographically dispersed suppliers. It may occur when suitable technological solutions, specialized capabilities, or competitive suppliers are not fully available within the local market (Uyarra et al., 2014; Herz & Varela-Irimia, 2020). By sourcing beyond local boundaries, purchasing regions gain access to suppliers endowed with more heterogeneous and cognitively distant knowledge bases (Zabala-Iturriagagoitia, 2022). This may disrupt the insularity of local innovation systems and expanding cross-regional knowledge exchange (Mason & Brown, 2013). Exposure to such external capabilities facilitates the recombination of distant knowledge and support entry into less related technological domains (Castaldi et al., 2015). These mechanisms may help purchasing regions loosen existing path dependence and increase the likelihood of path-breaking diversification.

This leads to the second hypothesis:

H2: *Compared with local procurement, non-local procurement in public procurement of innovation (PPI) is more likely to facilitate path-breaking technological diversification.*

4 Variable and Model Specification

4.1 Technological Diversification-related Variables

Utilizing the original data on authorized innovative patents from 2016 to 2021 sourced from National Intellectual Property Administration in China, we consolidated the number of innovative patent authorizations at the 4-digit IPC-city-year level. Subsequently, we constructed two key measures related to regional technological diversification: the revealed comparative advantage (*RCA*), and the relatedness density (*Density*).

(1) Revealed Comparative Advantage (*RCA*)

RCA is a binary variable derived from the location quotient. It signifies whether a city is specialized in a particular technological domain. Following Hidalgo et al. (2007), the definition of *RCA* is as follows:

$$RCA_{ict}=\begin{cases}=1,if\ \dfrac{Teconology_{ict}/\sum_i Teconology_{ict}}{\sum_C Teconology_{ict}/\sum_c\sum_i Teconology_{ict}}\geq 1\\ =0,if\ \dfrac{Teconology_{ict}/\sum_i Teconology_{ict}}{\sum_C Teconology_{ict}/\sum_c\sum_i Teconology_{ict}}<1\end{cases} \quad (1)$$

$Technology_{ict}$ is the quantity of authorized innovative patents for subclass in city *c* at a given time *t*. The equations suggest that city *c* has RCA_{ict} in technology *i* if its proportion of this technology, compared to all the technologies innovated within the city, exceeds the national average.

(2) Relatedness density (Density)

Relatedness density captures the extent to which a target technology is related to the technologies already present in a city's knowledge base. The relatedness density ($Density_{ict}$) is measured by:

$$Density_{ict}=\frac{\sum_j RCA_{jct}\varphi_{ijt}}{\sum_j \varphi_{ijt}} \quad (2)$$

$$\varphi_{ijt}=\min\{P(RCA_{ict}=1|RCA_{jct}=1),\ \ P(RCA_{jct}=1|RCA_{ict}=1)\} \quad (3)$$

φ_{ijt} is the lowest possibility that for technologies *i* and *j* to both be developed (where *RCA*=1) within the same city. A higher *Density* suggests that the target technology is more closely connected to the established technologies in city *c*, all of which share a similar knowledge foundation.

4.2 Public Procurement of Innovation

The procurement data are obtained from the China Government Procurement Website, the official platform on which Chinese governments publish procurement transaction records. The dataset contains more than two million records from 2016 to 2021. According to the Government Procurement Law, governments at all levels are required to disclose project information and supplier names on designated official media for public supervision. Each record therefore contains detailed information on the purchaser, supplier, contract amount, contract title, main item description, and technical or service requirements.

Following the PPI literature, we define public procurement of innovation (PPI) as government procurement that creates demand for technology-related, innovation-oriented goods, services, and solutions. Empirically, PPI is difficult to observe directly because procurement records do not explicitly label whether a contract is intended to promote innovation. We therefore identify PPI contracts through a text-based classification strategy that captures procurement items involving technology-intensive and innovation-related content.

The identification process involves three steps. First, we compile a comprehensive list of technology-intensive and innovation-related keywords by drawing on national procurement catalogues, industrial policy documents, and local innovation directories. Second, we construct a keyword database of more than 4,000 terms through AI-assisted filtering and manual validation. The keyword database covers categories such as information technology, digital platforms, intelligent equipment, software systems, data services, environmental technologies, R&D services, testing and inspection platforms, and other technology-intensive solutions. Third, we match these keywords against three key textual fields in all procurement contracts: Contract Title, Main Item Description, and Specifications or Service Requirements. Contracts containing at least one validated keyword in these fields are classified as PPI contracts.

To improve classification accuracy, we further conduct manual checks on ambiguous keywords and sampled contracts. This procedure helps reduce false positives and distinguish PPI from ordinary procurement such as office supplies, routine maintenance, and general administrative services. Then, following Lu and Wang (2022), we identify the locality of each purchaser and supplier and aggregate the transaction amounts of identified PPI contracts to the city-year level.

Based on the locality of the purchaser and the supplier, we further categorized a public procurement record as a local procurement (*Local-PPI*) if both the purchaser and supplier are from the same city. If they belong to different cities, we categorized the procurement as a non-local procurement (*Non-Local-PPI*). This distinction allows us to examine whether the effects of PPI on technological diversification vary across different spatial sourcing strategies.

4.3 Controls

To control for other influencing factors in the technology diversification process, we incorporated a set of technology- and city-level control variables:

(1) *GCI* measures the disparity between the city knowledge complexity index (KCI) and the technology complexity index (TCI).

(2) Gross Domestic Product (*GDP*) represents the city's economic development.

(3) Industrial structure (*Ind*) is measured by the ratio of the secondary industrial employment.

(4) Total Population (*Pop*) serves as an indicator of city size.

(5) Number of Secondary schools (*Edu*) gauges the city's availability of educational resources.

The variables *GCI, KCI*, and *TCI* are calculated based on patent data, with the detailed calculation procedure reported in the Appendix. Data for *GDP, Ind, Pop,* and *Edu* are sourced from the China City Statistics Yearbooks. *GDP*, *Pop*, and *Edu* are transformed into logarithmic form to reduce skewness.

Table 1 shows the descriptive statistics for all these variables.

Table 1. Descriptive statistic

Variable	Definition	Obs	Mean	Std. Dev.
Entry	Entry probability to new technological domain	540,248	0.104	0.305
PPI	Total transaction amount of public procurement of innovation (in log form)	540,248	5.738	4.991
Local-PPI	Total transaction amount of PPI from local procurement (in log form)	540,248	4.757	4.882
Non-Local-PPI	Total transaction amount of PPI from non-local procurement (in log form)	540,248	3.370	4.379
GCI	Disparity between City knowledge complexity index (KCI) and technology complexity index (TCI)		15.015	10.177
Density	Relatedness density	540,248	0.005	0.021
Log(GDP)	Gross domestic product (in log form)	535,579	7.548	0.980
Ind	Industrial structure	397,315	41.118	14.816
Log(Pop)	Total population (in log form)	398,359	5.930	0.704
Log(Edu)	Number of Secondary schools (in log form)	522,402	1.819	0.942

4.4 Model Specifications

We started our analysis using a linear probability model to explore whether PPI is associated with cities' entry into new technological domains and whether this association varies with technological relatedness. Our analytical sample includes only cities that participated in PPI activities, while those with no participation were excluded. The specification is presented as follows:

$$Prob(Entry_{ict}=1)=\alpha_0+\alpha_1*Log(PPI_{ct-1})+\alpha_2*Log(PPI_{ct-1})*Density_{ict-1}$$

$$+\alpha_3*Density_{ict-1}+\alpha_3*GCI_{ict-1}+\alpha_4*GCI\_sq_{ict-1}+\beta*X_{ct-1}+\delta_i+\partial_c+\mu_t+\varepsilon_{ict} \quad (4)$$

The variable $Entry_{ict}$ takes 1 if RCA_{ict-1}=0 but RCA_{ict}=1, signifying that city *c* did not have revealed comparative advantage in technology *i* in year *t-1*, but develops revealed comparative advantage in that technology in year *t*. It therefore captures whether technology *i* is a newly developed domain for city *c* at time *t*. α_1 estimates how PPI is associated with the probability of entering a new technological domain. α_2 on

$Log(PP_{ct\text{-}1})*Density_{ict_{-1}}$ estimate whether the association between PPI and technological entry varies across technologies with different levels of relatedness to the city's existing knowledge base. A negative coefficient suggests that PPI enables cities to enter less related technological domains, indicating a greater tendency toward path-breaking diversification. By contrast, a positive coefficient indicates that PPI may reinforce the ongoing path-dependent process. α_3 on $Density_{ict_{-1}}$ is expected to be positive and indicating that cities are generally more likely to enter technologies that are closely related to their existing knowledge base. $GCI_{ict_{-1}}$and $GCI\_sq_{ict\text{-}1}$ captures the nonlinear impact of GCI on the probability of entry. $X_{ct\text{-}1}$ are controls detailed in Section 4.3. To account for various unobserved factors, we incorporate fixed effects for city, technology, and year.

To test *H2* and distinguish whether the effect of PPI differs across spatial sourcing strategies, we replaced *Log(PPI)* in Equation (4) with *Log(Local-PPI)* and *Log(Non-Local-PPI)*.

5 Result and Discussion

5.1 The Overall Effect of PPI

Before conducting the formal econometric analysis, we first examine the relationship between technological relatedness and PPI, by comparing the probability of entry into new technological domains across deciles of *Density*. Cities are divided into high-PPI and low-PPI groups based on the median value of PPI as the cutoff. Figure 1 shows that the probability of entering new technological domains rises as *Density* increase. That is to say, cities are more likely to enter technological domains that are closely related to their existing knowledge base, indicating a path-dependent diversification process.

Notably, cities with higher levels of PPI consistently exhibit higher entry probabilities at lower density deciles in general, while showing lower entry probabilities at higher density deciles. This pattern suggests that PPI tends to weaken path-dependent diversification and encourages entry into less related technological domains without considering other factors.

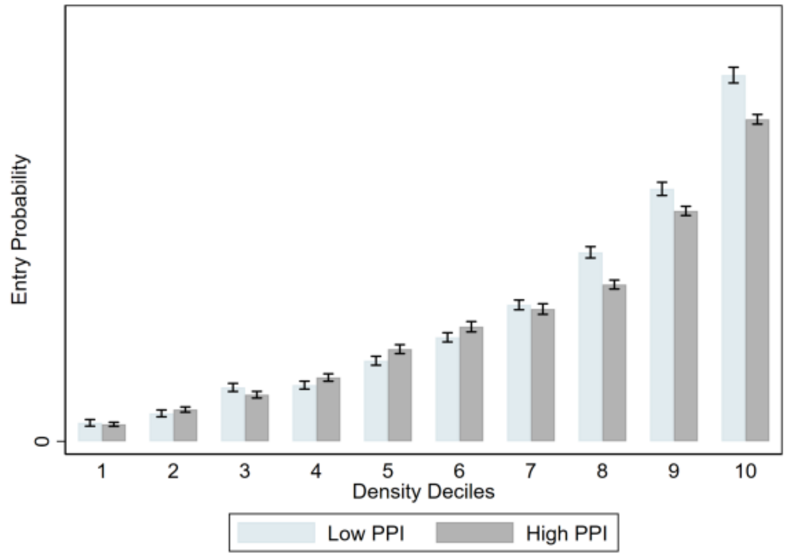

Figure 1. The new entry probability across *Density* deciles between high-PPI and low-PPI cities

Table 2 reports the linear probability model estimates of the effect of PPI on the probability of entering new technological domains. The significantly positive coefficient of *Density* shows that cities are more likely to enter new technological domains with a higher level of knowledge foundation relatedness, suggesting cities tend to venture into technological domains that align closely with their existing knowledge base. This finding is consistent with the path-dependent nature emphasized in the prior EEG research on diversification (Boschma & Capone, 2015; Zhu et al., 2017; Dong et al., 2025).

In Column (1), the coefficient on *Log(PPI)* is positive but statistically insignificant at the 5% level. In Column (2), the coefficient on *Log(PPI)* becomes significantly positive, while the coefficient on the interaction term *Log(PPI)* × *Density* is significantly negative. More specifically, when *Density* is below 0.70, the effect of PPI is positive; when *Density* exceeds 0.70, the effect becomes negative. These results suggest that, the association between PPI and technological entry is stronger for technologies with lower relatedness density, but weakens as technologies become more closely related to a city's existing knowledge base.

In other words, PPI encourages cities to expand into relatively less related technological domains, thereby fostering path-breaking rather than path-dependent diversification. Such results support Hypothesis 1 (***H1***), which posit that PPI fosters path-breaking technological diversification. These findings echo to existing literature, which suggests that PPI can stimulate demand, reduce uncertainty, and alleviate information asymmetry (Dai et al., 2021; Day & Merkert, 2023), thereby compensating for limited resources and capabilities required to develop path-breaking technologies.

Table 2. The correlation of PPI and technological entry

	(1)	(2)
VARIABLES	PPI	PPI
Log(PPI)	0.00130	0.00320***
	(0.00093)	(0.00084)
Log(PPI)×Density		-0.00458***
		(0.00084)
Density	0.16118***	0.16503***
	(0.00222)	(0.00231)
GCI	0.03229***	0.03296***
	(0.00173)	(0.00173)
GCI_sq	0.00105***	0.00108***
	(0.00006)	(0.00006)
Log(GDP)	-0.00476	-0.00677
	(0.00566)	(0.00568)
Ind	-0.00794***	-0.00867***
	(0.00270)	(0.00270)
Log(Pop)	0.11790***	0.12626***
	(0.02118)	(0.02125)
Log(Edu)	-0.00118	-0.00375
	(0.00616)	(0.00618)
Constant	0.07223***	0.07095***
	(0.00267)	(0.00265)
Observations	380,221	380,221
R-squared	0.10478	0.10487
City FE	Yes	Yes
IPC FE	Yes	Yes
Year FE	Yes	Yes

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All independent variables are lagged in one year. For comparability across models, all independent and control variables are standardized prior to estimation.

5.2 Main Result: Heterogeneity of Spatial Sourcing Strategies

As proposed in the theoretical framework ***H2***, different spatial sourcing strategies (local versus non-local) shape technological diversification differently. Thus, in this section, We further distinguish between local and non-local procurement to examine the heterogeneity of spatial sourcing strategies on technological diversification. The results are shown in Table 3.

In Column (1), the coefficient on *Log(Local-PPI)* is positive and significant, whereas the coefficient on *Log(Local-PPI) × Density* is negative but statistically insignificant. This result suggests that local procurement does not significantly promote path-breaking diversification. Rather, it may reinforce the path-dependent process of technological diversification by encouraging cities to enter domains that are more closely related to their existing knowledge base. In contrast, Column (2) shows that the coefficient on *Log(Non-Local-PPI)* is significantly positive, while the interaction term *Log(Non-Local-PPI) × Density* is significantly negative. This indicates that non-local procurement not only increases the probability of entering new technological domains but also promotes path-breaking diversification. This pattern implies that procuring innovative solutions from outside the local innovation system enables cities to overcome capability constraints and pursue more exploratory and unrelated technological opportunities. Such a result supports our Hypothesis 2(***H2)***.

Table 3. Heterogeneity of local and non-local procurement on technological entry

	(1)	(2)
VARIABLES	Local-PPI	Non-Local-PPI
Log(Local-PPI)	0.00137*	
	(0.00081)	
Log(Local-PPI)×Density	0.00147**	
	(0.00070)	
Log(Non-Local-PPI)		0.00272***
		(0.00076)
Log(Non-Local-PPI)×Density		-0.00154**
		(0.00067)
Observations	380,221	380,221
R-squared	0.10480	0.10481
City FE	Yes	Yes
IPC FE	Yes	Yes
Year FE	Yes	Yes

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All independent variables are lagged in one year. For comparability across models, all independent and control variables are standardized prior to estimation.

5.3 The IV analysis: Heterogeneity of Spatial Sourcing Strategies

Since PPI may be jointly determined with cities' innovation capacity, technological ambitions, or unobserved institutional conditions that influence both procurement intensity and diversification outcomes, endogeneity is a potential concern. To address it, we use the establishment of digital procurement centers as an instrumental variable for PPI, and conduct an IV analysis.

The establishment of digital procurement centers serves as a valid instrument for PPI for two reasons. First, it is exogenously correlated with the intensity and implementation quality of PPI, as digital procurement centers systematically expand the coverage, transparency, and operational capacity of procurement activities. Second, the establishment of these centers was largely driven by administrative modernization agendas, rather than by city-specific technological diversification strategies. Therefore, conditional on city, technology, and year fixed effects, the establishment of digital procurement centers is unlikely to affects cities' diversification directly, except through their impact on PPI, satisfying the exclusion restriction.

Table 4 reports the 2SLS estimates. The first-stage F-statistics are well above the conventional threshold, suggesting that weak-instrument concerns are unlikely to drive the estimates. The second-stage estimates reveal that, after accounting for potential endogeneity, different spatial sourcing strategies (local versus non-local) have distinct effects on technological diversification. Column (1) shows that the coefficient of *Log(Local-PPI)* is negative and statistically significant, while its interaction with *Density* is statistically insignificant. This indicates that, local procurement is associated with a lower probability of entering new technological domains in general, regardless of whether these domains are related or unrelated to their existing knowledge base. In other words, local procurement does not provide evidence of facilitating path-breaking diversification. By contrast, the insignificant positive coefficient on *Log(Non-Local-PPI)* and significant negative coefficient on *Log(Non-Local-PPI)×Density* in Column (2) show that, non-local procurement is more likely to facilitate entry into less related technological domains, supporting path-breaking diversification, further verifying Hypothesis 2 (***H2)***.

Taken together, Table 3 and Table 4 suggests that the effect of PPI on technological diversification depends critically on spatial sourcing strategies. Local procurement, although embedded within the regional innovation system, may introduce risks of duplication, corruption, and politically motivated or inefficient investments (Georghiou et al., 2014; Holma et al., 2022). Such risks can distort procurement objectives and undermine its innovation-enhancing potential (Kutlina-Dimitrova & Lakatos, 2016;

Day & Merkert, 2023), thereby limiting cities' ability to enter new technological domains or achieve path-breaking outcomes.

By contrast, non-local procurement provides an external channel for accessing diverse knowledge bases and technological capabilities. Procuring from outside the local system not only expands the pool of potential suppliers but also facilitates cross-regional knowledge flows and resource exchanges (Uyarra et al., 2014; Zabala-Iturriagagoitia, 2022), helping maintain competitive pressure in the market (Day & Merkert, 2023). These mechanisms allow cities to overcome constraints inherent in their existing technological trajectories and expose them to novel combinations of knowledge, thereby increasing new technological entry and fostering more path-breaking diversification.

Table 4. The IV estimates for the heterogeneity of local and non-local procurement on technological entry

VARIABLES	(1) 2nd Stage Entry	(2) 2nd Stage Entry
Log(PPI)	-0.05066**	
	(0.02078)	
Log(PPI) ×Density	0.00588	
	(0.00961)	
Log(Non-Local-PPI)		0.47205**
		(-0.2006)
Log(Non-Local-PPI)×Density		-0.21060**
		(-0.09022)
Observations	380,221	380,221
R-squared	0.10487	0.10487
City FE	Yes	Yes
IPC FE	Yes	Yes
Year FE	Yes	Yes
F-value of the first stage	1228.44	5073.65

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All independent variables are lagged in one year. For comparability across models, all independent and control variables are standardized prior to estimation.

5.4 Robustness Check

To ensure the robustness of the results, we conduct a series of robustness checks in Table 5. First, considering that technological entry may not be immediately stable and that the effect of PPI may take time to materialize, we adopt a stricter definition of technological entry, defining Entry2 as equal to 1 only if the *RCA* equals 0 in the previous two years and equals 1 in both the current and subsequent year. The results, reported in Columns (1)-(2), continue to show that non-local procurement is more strongly associated with path-breaking diversification.

Second, we use two-year lagged PPI variables to account for the potential time lag between procurement activities and technological diversification. The results are presented in Columns (3)-(4), and remain consistent with the baseline.

Third, given the binary nature of the dependent variable, we re-estimate the model using an Probit approach in Columns (5)-(6). In these specifications, the significant positive coefficient on *Log(Local-PPI)*×*Density* and significant negative coefficient on *Log(Non-Local-PPI)*×*Density* show that, non-local procurement is more effective in promoting path-breaking diversification.

Finally, we winsorize the local and non-local procurement variables at the 1% level to mitigate the influence of extreme values and report the results in Column (7)-(8). The results again confirm the baseline patterns, with non-local procurement consistently showing a larger positive effect on path-breaking diversification and a more pronounced negative interaction with density.

Across all robustness checks, these results reinforce our main conclusion that non-local procurement significantly stimulates path-breaking technological diversification to a larger extent than local procurement. This reinforces the argument that spatial sourcing strategies play an important role in shaping how PPI affects regional technological diversification.

Table 5. Robustness checks

VARIABLES	(1) Entry2	(2) Entry2	(3) lag 2 years	(4) lag 2 years	(5) probit	(6) probit	(7) winsor	(8) winsor
Log(Local-PPI)	0.00025		-0.00304***		-0.00118		0.00105	
	(0.00045)		(0.00115)		(0.00488)		(0.00084)	
Log(Local-PPI)×Density	0.00012		0.00037		0.01076***		0.00128*	
	(0.00040)		(0.00085)		(0.00404)		(0.00072)	
Log(Non-Local-PPI)		0.00068*		-0.00196*		0.01466***		0.00291***
		(0.00041)		(0.00113)		(0.00509)		(0.00077)
Log(Non-Local-PPI)×Density		-0.00117***		-0.00161*		-0.01007**		-0.00257***
		(0.00038)		(0.00095)		(0.00419)		(0.00072)
								(0.00072)
Observations	337,275	337,275	378,534	378,534	380,221	380,221	380,221	380,221
R-squared	0.04729	0.04732	0.10500	0.10500			0.10479	0.10483
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IPC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All independent variables are lagged in one year. For comparability across models, all independent and control variables are standardized prior to estimation.

5.5 Analysis from Supplier’ s perspective

In contrast to the previous analysis that adopts a purchaser-centric perspective, which enables access to external knowledge and supports path-breaking innovation, irrespective of the knowledge’s geographic origin. this section shifts the focus to the supplier side. Within purchaser-supplier relationships, suppliers typically occupy a subordinate position and are required to adhere closely to purchaser-defined specifications rather than (Gereffi et al., 2005). Therefore, the effect of PPI on supplying regions might be different.

Table 6 explores whether non-local procurement generates different implications for purchasing and supplying regions. The Columns (1) of Table 6 replicates the estimates from Column (2) of Table 3, where non-local procurement is analyzed from the purchaser-side perspective., suggesting that non-local procurement facilitates path-breaking diversification in purchasing regions. Column (2) shifts the analysis to the supplier side. The coefficients of *Log(Non-Local-PPI)* as well as the interaction term *Log(Non-Local-PPI) ×Density* are negative and statistically significant, suggesting that for supplying regions, non-local procurement does not appear to promote technological entry in overall, although this negative association is relatively weaker for less related technological domains.

Table 6. Analysis from supplier’s perspective

VARIABLES	(1) Purchaser	(2) Supplier
Log(Non-Local-PPI）	0.00272***	-0.00214***
	(0.00076)	(0.00075)
Log(Non-Local-PPI)×Density	-0.00154**	-0.00134*
	(0.00067)	(0.00072)
Observations	380,221	380,221
R-squared	0.10481	0.10483
City FE	Yes	Yes
IPC FE	Yes	Yes
Year FE	Yes	Yes

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All independent variables are lagged in one year. For comparability across models, all independent and control variables are standardized prior to estimation.

Taken together, Table 6 reveals an asymmetric pattern between purchasing and supplying regions: non-local procurement facilitates path-breaking diversification in purchasing regions, but its benefits for supplying regions are more constrained and do not generate technological diversification. Unlike purchasing regions, which use non-local procurement to access external knowledge and specialized capabilities, supplying regions occupy a subordinate position and are required to adhere closely to purchaser-defined specifications (Benner & Tushman, 2003; Iossa et al., 2018). As a result, PPI may encourage suppliers to mobilize existing technological strengths and proven solutions rather than broadly explore new technological domains. Especially in non-local procurement, to secure non-local contracts, suppliers prioritize exploiting existing technological strengths—emphasizing cost efficiency, reliability, and scale-rather than pursuing radical innovation (Uyarra et al., 2014). This may explain why non-local procurement is associated with a lower overall probability of technological entry in supplying regions. These findings suggest that PPI operates as a relational mechanism whose regional effects depend on whether a city occupies the purchaser or supplier position within the procurement relationship.

5.6 Additional Analysis: The effect of regular public procurement (RPP)

To assess whether the asymmetric effects identified above are specific to innovation-oriented PPI, we further examine how regular public procurement (RPP), affects the technological diversification process in Table 7. The results show that RPP exhibits markedly different patterns from those observed for PPI. The significant and positive coefficient of *Log(Local-RPP)×Density* in Column (1). indicates that RPP with local procurement significantly reinforces path-dependent diversification, that is, cities are more likely to enter technological domains closely related to their existing knowledge base. While RPP with non-local procurement also shows a positive association with path-dependent diversification, the coefficient of *Log(Non-Local-RPP)×Density* is insignificant in Column (2).

These findings highlight that PPI differs from RPP not only in its policy objective, but also in its relationship with regional technological diversification. Unlike PPI, which is explicitly designed to stimulate innovation and can therefore promote path-breaking activities, RPP refers to the acquisition of goods and services already available in the market, without a specific focus on promoting technological innovation. RPP primarily focuses on standardized products with limited technological potential (Caravella & Crespi, 2021), which may divert firms toward routine operations rather than pursuing innovative technological advancements (Krieger et al., 2024). As a result, RPP with local procurement tends to reinforce existing technological trajectories, while non-local RPP weakly mitigates this path dependence, and does not meaningfully induce path-breaking diversification in the way that non-local PPI does. To some extent, this pattern is consistent with our main findings of PPI, which show that non-local procurement serves as a conduit for novel knowledge and facilitates broader resource exchanges, thereby facilitating technological diversification into more challenging and radical domains.

Table 7. The effect of regular public procurement (RPP)

	(1)	(2)
VARIABLES	RPP	RPP
Log(Local-RPP)	-0.06210***	
	(0.01040)	
Log(Local-RPP)×Density	0.00938***	
	(0.00221)	
Log(Non-Local-RPP)		-0.00052
		(0.00112)
Log(Non-Loca-RPP)×Density		0.00099
		(0.00154)
Observations	380,221	380,221
City FE	Yes	Yes
IPC FE	Yes	Yes
Year FE	Yes	Yes
F-value of the first stage	0.10485	0.10478

6 Discussion and Conclusion

Public procurement of innovation (PPI) is widely recognized as an effective demand-side policy tool capable of stimulating innovation (Uyarra et al., 2020; Day & Merkert, 2023). However, its effects on regional technological diversification remain insufficiently understood. In particular, existing research has paid limited attention to whether PPI helps regions move beyond established technological trajectories, and whether its effects vary across different spatial sourcing strategies. Utilizing a novel dataset of over 2.24 million annual public procurement contracts and 2.41 million patent data from Chinese cities spanning 2016 to 2021, this study examines how PPI affects technological diversification, with particular attention to local and non-local procurement and to the asymmetric positions of purchasing and supplying regions.

The results highlight three key findings. First, PPI facilitates path-breaking technological diversification in general, by induces cities to expand into less related technological domains. Second, its effects are highly contingent on spatial sourcing strategies. Compared with local procurement, non-local procurement is more likely to facilitate path-breaking technological diversification in purchasing regions. Third, the benefits of non-local procurement are not symmetrically distributed across interregional procurement relationships. While purchasing regions benefit from diversification into less related technological domains, these positive effects do not spill over to supplying regions in the form of broader technological diversification.

These findings have several important implications for debates in evolutionary economic geography concerning path dependence, path-breaking diversification, and the role of external relationships in regional technological evolvement. First, the results challenge the common assumption that PPI automatically promotes innovation. PPI with local procurement does not provide evidence of facilitating path-breaking diversification. This finding aligns with evolutionary economic geography arguments that diversification processes are deeply path dependent and anchored in inherited knowledge structures (Boschma, 2016; Balland & Boschma, 2021; Quatraro & Scandura, 2024; Dong et al., 2025; Lo Conte et al., 2025). When procurement demand is repeatedly directed toward local suppliers, innovation incentives tend to concentrate within established technological domains, reinforcing existing supplier structures, reducing competitive pressure, and limiting exposure to external knowledge. From this perspective, local procurement, while often justified on place-based development grounds (Patrucco et al., 2024; Brunjes & Rodriguez-Plesa, 2024), may have unintended consequences for long-term technological diversification.

Second, the study highlights the role of non-local procurement as a tool for path-breaking diversification in purchasing regions. Procuring from outside the local innovation system allows public purchasers to access to more heterogeneous and cognitively distant knowledge bases (Uyarra et al., 2014; Herz & Varela-Irimia, 2020; Zabala-Iturriagagoitia, 2022). These external inputs may relax local capability constraints and supports diversification into less related technological domains. In this sense, PPI should not be understood only as a place-based policy instrument operating within a local innovation system. It is also a relational mechanism embedded in interregional procurement relationships, enabling purchasing regions to pursue more exploratory innovation trajectories.

Third, the study reveals a pronounced asymmetry in the effects of non-local procurement between purchasing and supplying regions. Non-local procurement promotes path-breaking diversification in purchasing regions, but it does not generate the same effect in supplying regions. For suppliers, external procurement contracts may require compliance with purchaser-defined specifications, delivery standards, and administrative requirements. Such contracts may encourage firms to mobilize existing technological strengths and proven solutions rather than broadly explore new technological domains (Benner & Tushman, 2003; Karttunen et al., 2022; Uyarra et al., 2014; Iossa et al., 2018). This suggests that interregional procurement relationships can redistribute opportunities for technological upgrading unevenly across regions.

The findings above carry significant implications for practice. First, to avoid unintentionally path-dependent long-term technological development, policymakers should adopt innovation-oriented evaluation criteria in local procurement. Local procurement can support coordination and reduce transaction costs, but it may also reinforce inherited technological trajectories. To avoid this risk, local procurement should incorporate evaluation criteria that reward novelty, learning potential, and technological upgrading rather than relying primarily on past performance or local familiarity. Second, non-local procurement should be recognized as a strategic instrument for accessing external capabilities and promoting path-breaking diversification. Policymakers should support and scale up non-local procurement by establishing interregional procurement cooperation platforms that lower information barriers and transaction costs for non-local suppliers, enhancing the alignment between procurement demand and geographically dispersed technological capabilities. Third, in response to the pronounced asymmetry in non-local procurement effects, supplying regions should proactively implement complementary measures to convert procurement participation into broader technological upgrading. They are supposed to strengthen local innovation networks, support knowledge intermediaries, and improve firms' absorptive capacities. By enhancing the local diffusion and recombination of knowledge generated through procurement activities, such efforts can ensure that this knowledge translates into broader technological development.

This study has several limitations that open avenues for future research. First, the analysis focuses on patent-based technological entry. Patents provide a useful measure of technological diversification (Lu & Wang, 2022; Dong et al., 2022, 2025; Wei et al., 2025), but they may not capture all forms of innovation, especially service innovation, organizational innovation, or non-patented technological learning. Future research could incorporate alternative innovation indicators to better capture the dynamic effects of PPI. Second, this study identifies the heterogeneous effects of local and non-local procurement, but it does not directly observe the micro-level learning mechanisms through which procurement relationships shape regional technological diversification. This remains an important direction for future research.

Reference

Anderson, R., Kovacic, W., & Muller, A. (2012). Ensuring integrity and competition in public procurement markets: A dual challenge for good governance. In United Nations Office for Project Services (Ed.), *Transparency and public procurement* (pp. 9-11).

Ao, R., Zhong, L., Chen, J., Li, X., & Zhou, X. (2026). Is the occupational evolution of Chinese cities driven by industrial structures? Insights from industry-occupation cross-relatedness. *Journal of Regional Science, 66*(1), 293-314.

Balland, P.A., & Boschma, R. (2021). Mapping the potentials of regions in Europe to contribute to new knowledge production in Industry 4.0 technologies. *Regional Studies, 55*, 1652-1666.

Balland, P.A., & Rigby, D. (2017). The geography of complex knowledge. *Economic Geography, 93*, 1-23.

Balland, P.A., Boschma, R., Crespo, J., & Rigby, D. (2018). Smart specialization policy in the European Union: Relatedness, knowledge complexity and regional diversification. *Regional Studies, 53*(9), 1252-1268.

Barca, F., McCann, P., & Rodríguez-Pose, A. (2012). The case for regional development intervention: Place-based versus place-neutral approaches. *Journal of Regional Science, 52*(1), 134-152.

Benner, M. J., & Tushman, M. L. (2003). Exploitation, exploration, and process management: The productivity dilemma revisited. *Academy of Management Review, 28*(2), 238-256.

Boschma, R. (2016). Relatedness as driver of regional diversification: A research agenda. *Regional Studies, 51*(3), 351-364.

Boschma, R., Balland, P. A., & Kogler, D. (2015). Relatedness and technological change in cities: The rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. *Industrial and Corporate Change, 24*(1), 223-250.

Breschi, S., Lissoni, F., & Malerba, F. (2003). Knowledge-relatedness in firm technological diversification. *Research Policy, 32*(1), 69-87.

Brunjes, B. M., & Rodriguez-Plesa, E. (2024). Equity in government contracting: Analyzing the performance of small disadvantaged businesses. *Public Administration Review, 84*, 484-499.

Caravella, S., & Crespi, F. (2021). The role of public procurement as innovation lever: Evidence from Italian manufacturing firms. *Economics of Innovation and New Technology, 30*, 663-684.

Castaldi, C., Frenken, K., & Los, B. (2015). Related variety, unrelated variety and technological breakthroughs: An analysis of US state-level patenting. *Regional Studies, 49*(5), 767-781.

Castelnovo, P., Clò, S., & Florio, M. (2023). A quasi-experimental design to assess the innovative impact of public procurement: An application to the Italian space industry. *Technovation, 121*, 102683.

Chen, Y., Tan, J., & Yang, R. (2025). Technological relatedness, technological complexity and the development of digital technology in Chinese cities. *Applied Geography, 179*, 103635.

Crespi, F., & Guarascio, D. (2019). The demand-pull effect of public procurement on innovation and industrial renewal. *Industrial and Corporate Change, 28*, 793-815.

Czarnitzki, D., Hünermund, P., & Moshgbar, N. (2020). Public procurement of innovation: Evidence from a German legislative reform. *International Journal of Industrial Organization, 71*, 102620.
Dai, X., Li, Y., & Chen, K. (2021). Direct demand-pull and indirect certification effects of public procurement for innovation. *Technovation, 101*, 102198.
Day, C. J., & Merkert, R. (2023). Unlocking public procurement as a tool for place-based industrial strategy. *Regional Studies, 57*, 1029-1042.
Dong, Z., Shen, H., Zhang, W., Wu, R., & Wang, S. (2022). How does resource dependence relate cities' technology diversification? The role of density and complexity. *Cities, 130*, 103883.
Dong, Z., Sun, S., Balland, P.-A., & Zhang, W. (2025). Environmental regulation promotes green technological diversification: Evidence from Chinese cities. *Regional Studies, 59*, 2488207.
Eckersley, P., Flynn, A., Lakoma, K., & Ferry, L. (2023). Public procurement as a policy tool: The territorial dimension. *Regional Studies, 57*, 2087-2101.
Edler, J., & Georghiou, L. (2007). Public procurement and innovation: Resurrecting the demand side. *Research Policy, 36*(7), 949-963.
Edquist, C., & Hommen, L. (2000). Public technology procurement and innovation theory. In C. Edquist, L. Hommen, & L. Tsipouri (Eds.), *Public technology procurement and innovation* (pp. 5-70). Springer.
Edquist, C., & Zabala-Iturriagagoitia, J. M. (2020). Functional procurement for innovation, welfare, and the environment. *Science and Public Policy, 47*, 595-603.
Georghiou, L., Edler, J., Uyarra, E., & Yeow, J. (2014). Policy instruments for public procurement of innovation: Choice, design and assessment. *Technological Forecasting and Social Change, 86*, 1-12.
He, C., & Zhang, W. (2021). Path transplantation: How to use the power of irrigation—A case study of the photovoltaic industry in China. *The Geographical Journal, 187*(4), 301-314.
Herz, B., & Varela-Irimia, X.-L. (2020). Border effects in European public procurement. *Journal of Economic Geography, 20*(6), 1359-1405.
Hidalgo, C. A., Klinger, B., Barabási, A.-L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science, 317*(5837), 482-487.
Holma, A.-M., Østensen, M. W., Holmen, E., & de Boer, L. (2022). Market dialogue in public procurement: Buyer-supplier interfaces and relational abilities. *Industrial Marketing Management, 104*, 51-67.
Iossa, E., Biagi, F., & Valbonesi, P. (2018). Pre-commercial procurement, procurement of innovative solutions and innovation partnerships in the EU: Rationale and strategy. *Economics of Innovation and New Technology, 27*(8), 730-749.

Karttunen, E., Matela, M., Hallikas, J., & Immonen, M. (2022). Public procurement as an attractive customer: A supplier perspective. *International Journal of Operations & Production Management, 42*(13), 79-102.

Koster, H. R. A., Cheng, F., Gerritse, M., & van Oort, F. (2019). Place-based policies, firm productivity, and displacement effects: Evidence from Shenzhen, China. *Journal of Regional Science, 59*, 187-213.

Krieger, B., Prüfer, M., & Strecke, L. (2024). *Public procurement can hinder innovation*. Working Papers of ECOOM-Centre for Research and Development Monitoring.

Kutlina-Dimitrova, Z., & Lakatos, C. (2016). Determinants of direct cross-border public procurement in EU member states. *Review of World Economics, 152*, 501-528.

Lember, V., Kalvet, T., & Kattel, R. (2011). Urban competitiveness and public procurement for innovation. *Urban Studies, 48*, 1373-1395.

Lerusse, A., & Van de Walle, S. (2022). Buying from local providers: The role of governance preferences in assessing performance information. *Public Administration Review, 82*, 835-849.

Li, S., He, C., Sheng, H., Li, W., & Luan, X. (2026). Cross-industry adoption of advanced manufacturing technologies within cities: Evidence from industrial robots in China. *Cities, 176*, 107258.

Liu, J., Huang, Y., Zhu, S., & He, C. (2026). Public procurement, institutional distance and cross-regional subsidiary location choice. *Regional Studies, 60*(1).

Lo Conte, G., Mina, A., & Rocchetta, S. (2025). Turning technological relatedness into industrial strategy: The productivity effects of smart specialization in Europe. *Economic Geography, 101*(1), 28-59.

Lu, S., & Wang, H. (2022). How political connections exploit loopholes in procurement institutions for government contracts: Evidence from China. *Governance, 36*, 1205-1224.

MacKinnon, D., Dawley, S., Pike, A., & Cumbers, A. (2019). Rethinking path creation: A geographical political economy approach. *Economic Geography, 95*(2), 113-135.

Markard, J., Raven, R., & Truffer, B. (2012). Sustainability transitions: An emerging field of research and its prospects. *Research Policy, 41*(6), 955-967.

Martin, H., Martin, R., & Zukauskaite, E. (2019). The multiple roles of demand in new regional industrial path development: A conceptual analysis. *Environment and Planning A: Economy and Space, 51*(8), 1741-1757.

Martin, R., & Martin, H. (2023). The role of demand in regional industrial path development: Examples from the Swedish periphery. *European Planning Studies, 31*(9), 1975-1992.

Mason, C., & Brown, R. (2013). Creating good public policy to support high-growth firms. *Small Business Economics, 40*, 211-225.

Mu, E., Zhu, S., Sheng, H., & He, C. (2026). Chasing the sun: How does policy-induced local demand promote the spatio-temporal evolution of China's solar photovoltaic industry. *Environmental Innovation and Societal Transitions, 58*, 101045.
Neffke, F., Henning, M., & Boschma, R. (2011). How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography, 87*, 237-265.
Nilsson, M., Schubert, T., & Miörner, J. (2025). The productivity effects of regional anchors on local firms in Swedish regions between 2007 and 2019: Evidence from an expert-informed machine learning approach. *Journal of Economic Geography, 25*(2), 215-234.
Obwegeser, N., & Müller, S. D. (2018). Innovation and public procurement: Terminology, concepts, and applications. *Technovation, 74*, 1-17.
Pinheiro, F. L., Balland, P. A., Boschma, R., & Hartmann, D. (2022). The dark side of the geography of innovation: Relatedness, complexity and regional inequality in Europe. *Regional Studies, 59*(1), 2106362.
Quatraro, F., & Scandura, A. (2024). The contribution of academic inventors to regional technological diversification: The Italian evidence. *Journal of Economic Geography, 24*(6), 785-819.
Radicic, D. (2019). Effectiveness of public procurement of innovation versus supply-side innovation measures in manufacturing and service sectors. *Science and Public Policy, 46*, 732-746.
Rivers, D., & Vuong, Q. H. (1988). Limited information estimators and exogeneity tests for simultaneous probit models. *Journal of Econometrics, 39*(3), 347-366.
Similä, J. O., & Mwesiumo, D. (2024). Implementing public procurement of green innovations: Does structural alignment matter? *Journal of Cleaner Production, 461*, 142562.
Stojčić, N., Srhoj, S., & Coad, A. (2020). Innovation procurement as capability-building: Evaluating innovation policies in eight Central and Eastern European countries. *European Economic Review, 121*, 103330.
Sunley, P., Martin, R., Gardiner, B., & Pike, A. (2020). In search of the skilled city: Skills and the occupational evolution of British cities. *Urban Studies, 57*(1), 109-133.
Turkina, E., Frigon, A., & Doloreux, D. (2025). Network versus spatial proximity and firm innovation: The case of the R&D service sector. *Journal of Regional Science*, 65(1), 135-155.
Uyarra, E., & Flanagan, K. (2010). Understanding the innovation impacts of public procurement. *European Planning Studies, 18*, 123-143.
Uyarra, E., Edler, J., Garcia-Estevez, J., Georghiou, L., & Yeow, J. (2014). Barriers to innovation through public procurement: A supplier perspective. *Technovation, 34*, 631-645.

Uyarra, E., Zabala-Iturriagagoitia, J. M., Flanagan, K., & Magro, E. (2020). Public procurement, innovation and industrial policy: Rationales, roles, capabilities and implementation. *Research Policy, 49*, 103844.
Van Winden, W., & Carvalho, L. (2019). Intermediation in public procurement of innovation: How Amsterdam's Startup-in-Residence Programme connects startups to urban challenges. *Research Policy, 48*, 103789.
Wei, J., Sun, J.-Y., Li, Y., & Du, Y. (2025). Does greater knowledge complexity promote structural upgrading? Evidence from Chinese cities. *Journal of Regional Science, 65*, 1058-1076.
Zabala-Iturriagagoitia, J. M. (2022). Fostering regional innovation, entrepreneurship and growth through public procurement. *Small Business Economics, 58*, 1205-1222.
Zhang, P., & He, C. (2026). Breaking through the evolutionary path: Market potential and regional industrial dynamics. *The Annals of Regional Science, 75*, 82.
Zhang, P., He, C., & Sheng, H. (2024). Market relatedness and local export dynamics: Evidence from China. *Applied Geography, 164*, 103218.
Zhao, X., Li, X., Wu, Y., Qiao, L., & Zhang, C. (2025). Assessment of the effects of China's new energy vehicle industry policies: From the perspective of moderating effect of consumer characteristics. *Environment, Development and Sustainability, 27*(2), 4319-4340.
Zhu, S., He, C., & Zhou, Y. (2017). How to jump further and catch up? Path-breaking in an uneven industry space. *Journal of Economic Geography, 17*(3), 521-545.

Appendix 1: Knowledge Complexity Index (*KCI*) and Technology Complexity Index (*TCI*)

We adopted the 'Method of Reflections' introduced by Hidalgo and Haussmann (2009) to formulate a complexity index at both the city and technology levels. The degree of complexity is influenced by two key factors: (i) The diversity of technology within a city. A city with higher complexity has specializations across a broad range of technological fields, implying a higher degree of diversity. (ii) The ubiquity of a technology. Technologies with greater complexity are limited to fewer regions (signifying lower ubiquity) because of the requisite specialized knowledge and skills. The detailed specification is as follows:

$$Diversity_{c,t}=K_{c,t}=\sum_c M_{i,c,t}$$

$$Ubiquity_{i,t}=K_{i,t}=\sum_i M_{i,c,t}$$

$M_{i,c,t}$ in city-technology adjacency matrix equals 1 if $RCA_{i,c,t}$ takes 1, and equals 0 otherwise. Cities can be more complex by specializing in less exclusive technologies that are hardly to be found in other cities. Therefore, *TCI* and *KCI* can be generated by an iteration process as below:

In the city-technology adjacency matrix $M_{i,c,t}$, a value is assigned as 1 if $RCA_{i,c,t}$ takes 1 and 0 otherwise. Cities can achieve higher complexity by focusing on technologies that are rare or scarcely present in other cities. As a result, *TCI* and *KCI* can be derived through the iterative process described below:

$$KCI_{c,t}=K_{c,n,t}=\frac{1}{k_{c,0}}\sum_i M_{i,c,t}TCI_{i,n\text{-}1,\mathrm{t}}$$

$$TCI_{i,t}=K_{i,n,t}=\frac{1}{k_{i,0}}\sum_c M_{i,c,t}KCI_{c,n\text{-}1,\mathrm{t}}$$

We then established an index at the city-patent-year level to measure whether technology i surpasses the complexity of the city's existing knowledge portfolio by calculating the disparity between TCI_i and KCI_c.

$$GCI_{i,c,t}=TCI_{i,t}\text{-}KCI_{c,t}$$