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Agglomeration spillover, Accessibility by High-Speed Rail, and Urban Innovation in China: A focus on the Electronic Information Industry

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Conflict of Interest

There are no competing interests to declare.

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Highlights

Overall economic size and industrial specialization of a city matter for innovation

Science or engineering universities/research institutions are key to urban innovation

Local producer service sectors positively affect urban innovation outputs

Inter-city accessibility measured at more than 2-hour HSR time matters for innovation

Cities of 1-3 million people benefit most from inter-city accessibility in innovation

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Abstract

This study examines the impacts of different sources and types of agglomeration economies on urban innovation in the context high-speed rail (HSR), using the Electronic Information (EI) industry in China as an example. The impacts of inter-city access to different innovation factors such as knowledge sources (e.g., universities/research institutions), human capital (scientific/technical workers), input suppliers (e.g., producer services) and final markets through HSR networks are explored while local agglomeration effects and local proximity to HSR stations are controlled. Historical courier routes and stations and landform characteristics are used to construct instruments for endogenous HSR accessibility measures. Results indicate that local agglomeration benefits such as overall urban size, level of industrialization specialization and local access to top science/engineering universities/research institutions and producer service suppliers are positively associated with innovation performance in the EI sector. When longer travel time thresholds (e.g., > 2 hours) are applied, inter-city access to knowledge sources, human capital, producer services and final customers through HSR network yields significant impacts on innovation outputs of Type-II large cities (population in 1-3 million).

1. Introduction

Endogenous innovation has long been considered as an important source of stimulating economic development (Fagerberg et al., 2010, Fischer and Suarez-Villa, 1999, Grossman and Helpman, 1994). It not only depends on the performance of individual actors (e.g., firms, customers, universities/research institutions, government institutions) but also the ongoing collaborations and interactions between them (Andersson and Karlsson, 2004, 2006; Giuliano et al., 2019). Cities with larger concentrations of various actors and economic activities are more likely to become the hubs of innovation (Carlino and Kerr, 2015). While the effects of spatial agglomeration on urban growth, productivity and innovation have been widely examined, empirical studies usually considered cities (or regions) as club goods and applied a "catch-all" type measures of agglomeration economies (e.g., overall size, scale of density of cities) (Rosenthal and Strange, 2003; Graham and Melo, 2011). Only a few studies have explored the underlying causal mechanisms of agglomeration economies and possibilities of those spillover effects across cities (e.g., Echeverri-Carroll and Brennan, 1999; Breschi and Lissoni, 2001; Andersson and Karlsson, 2004; Carlino and Kerr, 2015; Zheng and Du, 2020).

Transportation investment also plays important roles in urban growth and innovation. Developed from new transportation technology, high-speed rail (HSR) could significantly reduce travel time and increase inter-city/inter-region connectivity, which may generate wider economic effects on cities directly or indirectly connected by it (Ureña et al., 2009, Garmendia et al., 2012, Hall, 2009). Knowledge-related sectors that have higher requirements for knowledge exchange and human interactions are expected to be more sensitive to HSR investment compared with traditional manufacturing industries (Chen and Vickerman, 2017). Yet there are only a few empirical evidence on the impacts of HSR networks on urban knowledge production or innovation outcomes (e.g., Inoue et al., 2017; Qingsong et al., 2018; Dong et al., 2020; Gao and Zheng; 2020). The effects of HSR on the microfoundations of agglomeration economies—the “intermediate stage” of HSR’s economic effects (Graham and Melo, 2011) — are not often discussed in empirical studies, either.

This study aims to contribute to empirical studies on the relationships between transport investments, agglomeration economies and urban innovation by focusing on the role of HSR in the China context. Using the electronic information (EI) industry as an example, this study examines how HSR investment in China affects urban innovation by linking with different sources of agglomeration economies (e.g., access to different input and output markets, specialized labors, and knowledge sources) and how the spatial extents of different sources of agglomeration economies outcomes vary in the context of HSR. Specifically, indices of transport accessibility to different resources and markets are employed to measure agglomeration economies arise from inter-city interaction opportunities associated with HSR investments. The relative locations of HSR stations within cities are also controlled to explore whether innovation activities prefer locations around HSR stations at the local level. The empirical findings would help us better understand the nature of agglomeration spillover effects and the mechanisms of transport investments in promoting urban growth and innovation.

We focus on urban innovation in China. Since 2006, the country has set up the goal of building an innovative nation and improving its indigenous innovation capacity. Cities are the basic units of implementing the innovation strategies and innovative pilot cities has been set up since 2008. In parallel to the innovation strategy, the construction of new HSR in China has been initiated in 2008. In the 2016 revised railway network plan, the role of HSR in leading China’s spatial economic development has been emphasized (Chen, 2012). Cities in China thus provide good examples to examine the economic benefits of HSR through the lens of innovation.

Another contribution of this study is to test how different sources of inter-city agglomeration economies in the context of HSR vary among cities of different size classes. In theory, it is often predicted that small and medium sized cities may “borrow size” from nearby higher-order cities to draw on the agglomeration benefits of those cities (Echeverri-Carroll and Brennan, 1999). With the introduction of HSR networks, cities may experience changes in inter-city accessibility and experience economic benefits to different degrees, depending on their relative size and locations (Ureña et al., 2009). This study is the first one in China’s to explicitly examine this issue. The results add to the empirical evidence on the spatial determinants of urban innovation and HSR’s wider economic effects in China and provide some insights for future spatial planning of HSR network and innovation centers across Chinese cities.

The rest of the paper is structured as follows. Section 2 reviews the literature on the role of agglomeration spillover and high-speed rail development in urban innovation. Section 3 discusses the research design, data, and methodology, Section 4 discusses the results. Section 5 concludes with the main findings and the associated policy implications.

2. Literature review

This section reviews the theoretical foundations of agglomeration effects on urban innovation at different spatial scales (e.g., intra-city vs. inter-city) and the underlying mechanisms of how transport investments influence urban growth and innovation through agglomeration economies. Recent empirical evidence concerning the wider economic impacts of HSR in China are also briefly discussed to identify the gaps in the existing studies and derive the potential role of HSR in inter-city agglomeration economies and urban innovation.

2.1 Links between agglomeration economies and innovation

Theories of agglomeration economies have long emphasized that spatial agglomeration of economic activities creates spillovers that lowered the costs of interactions and complementary activities. Tracing back to Marshall's (1920) seminal work, input sharing, labor market pooling, and knowledge spillover are three main sources of agglomeration economies on the production side. For the innovation process, spatial proximity to a greater pool of suppliers of intermediate inputs would allow firms to design and commercialize new products/process at lower costs (Helsley and Strange, 2002). Proximity to labor pool may reduce firms' training and searching costs for labors with specific skills matching their production and innovation requirements (Montgomery, 1988; Rosenthal and Strange, 2004). The third source—knowledge spillover—has the closest connection with innovation activities (Parr, 2004; Carlino and Kerr, 2015; Agrawal et al., 2017). Fischer (2001) summarized that in a localized innovation system, firms benefit from being close to their competitors and a set of actors, including suppliers, scientific workers, producer services, and industrial customers, not only because of reduced costs but also increased interactions and learning opportunities. For example, firms in large cities may have more opportunities to imitate, import, modify and diffuse new technologies from other firms and receive assistance or supports from producer service providers in the innovation process, such as financial, legal, and technical advice or accounting, marketing, and training services related to the introduction of new products or processes (Fischer, 2001). For local workers in large cities, easy access to experienced or high-human capital workers generates great learning opportunities, which also contributes to the overall stock of human capital of the city and facilitates the foster of new knowledge (Helsley and Strange, 2002; Carlino and Kerr, 2015).

Universities (or other academic institutions) provide one primary source of knowledge that can spill over to local economic agents through, for example, informal face-to-face contacts between employees and university researchers and meetings/seminars (Audretsch and Feldman, 2004; Breschi and Lissoni, 2001; Lin et al., 2007). Except for those non-market social interactions, there are also market-based mechanisms of knowledge flows (Audretsch and Feldman, 2004, Breschi and Lissoni, 2001). Breschi and Lissoni (2001) summarize that knowledge is "embodied in individual scientists and research teams (p.21)". To gain access to such knowledge and build up their innovation capacity, firms may establish transaction-intensive relationships with local academic institutions, such as obtaining consulting service and highly skilled workers from them or directly investing in local institutions' research projects (Breschi and Lissoni, 2001). Local university researchers may also directly appropriate their own research outputs by starting up their own business or transacting those results with existing firms (Breschi and Lissoni, 2001; Audretsch and Feldman, 2004). Another mechanism of the inter-firm knowledge diffusion is through the mobility of talented workers who embody relevant knowledge (Audretsch and Feldman, 2004; Breschi and Lissoni, 2001; Carlino and Kerr, 2015).

On the consumption side, the spatial agglomeration of consumers or firms (as purchasers of business services) would support "niche markets" and increase the variety of local goods and services available (Tabuchi and Yoshida 2000; Giuliano et al., 2019). Being proximity to a large local market also allows firms to test the potential success of a prototype product and receive quick feedbacks from customers that may help improve the new products and better position the products in the markets (Feldman, 1994; Carlino and Kerr, 2015).

Though the role of spatial proximity in facilitating opportunities of interaction among economic agents or actors has been emphasized, the exact spatial extents of agglomeration economies are not well identified in theories. For example, studies on innovation systems define the geographic boundaries of an innovation system ranging from nations, regions, and metropolitan areas/cities

(Andersson and Karlsson, 2006). Empirical studies suggest that the spatial extent of different sources of agglomeration economies differ. For example, labor market pooling and home market effect are usually defined at the metropolitan/city-wide scale because commuters or consumers mostly accept a travel distance within a city/metropolitan area (Andersson and Karlsson, 2004; Giuliano et al., 2019). The spatial extent of input sharing effects may vary with the production technology, the types of goods and services transported, and the associated transport costs (Scott 1988, Drucker 2012).

Similarly, knowledge spillover effects may also be spatially localized (e.g., at the neighborhood level). This may be because the transfer of tacit knowledge such as skills and routines that are context-based typically demands direct and repeated face-to-face interactions, the opportunities of which are likely to decay quickly with distance (Drucker 2012; Giuliano et al., 2019). Based on the above discussions, knowledge flows may also occur through transaction relationships such as purchasing of consulting or training services from universities and mobility of scientific or other skilled workers. This implies that such spillover effects may not be strictly spatially constrained within a city or region (Echeverri-Carroll and Brennan, 1999; Audretsch and Feldman, 2004; Breschi and Lissoni, 2001; Carlino and Kerr, 2015). The relative importance of local (e.g., city-wide) and non-local (e.g., inter-urban) knowledge spillover, however, is associated with the position of a city in the urban hierarchy (Andersson and Karlsson, 2004): while firms in larger or higher-order (larger) cities can rely on local knowledge sources and human capital pool, those in smaller or lower-order cities may benefit from spillover effects from higher-order cities by establishing knowledge linkages with other firms or universities in those cities. Another important channel for firms in small and medium-sized regions to access new knowledge and information is through the "customer-deliverer links" to other (larger) regions, which provide information about consumer demands of a broader market and the technical solutions of meeting those demands (Andersson and Karlsson, 2006).

2.2 Transportation infrastructure, inter-city accessibility, and innovation

Agglomeration economies and innovation depend on interactions between firms, workers, and other facilities which is facilitated by spatial proximity and likely to decrease with distance because transport movements across space are time and resources consuming (Andersson and Karlsson, 2004; Graham and Melo, 2011). Transportation infrastructure would influence the sources of agglomeration economies and innovation by substituting spatial proximity and easing access to various resources and actors (Graham and Melo, 2011). On the one hand, transportation improvements may strengthen agglomeration economies by facilitating flows of people, goods, and information within a city/region (Graham and Melo, 2011; Agrawal et al., 2017). On the other hand, transportation improvements may extend the geographic scope of agglomeration benefits and enhance inter-city interactions (Andersson and Karlsson, 2004).

Some of the benefits from transportation improvements are more related with input sharing and labor marketing pooling and final market access. For example, by reducing the costs of transporting inputs and outputs, transportation investments such as road and rail improvements may ease access to suppliers of intermediate inputs, service providers, and customers within a city (Graham and Melo, 2011) as well as open up new resources/inputs and larger and more differentiated markets outside of the city (Holl, 2004). While the former may reduce the uncertainties of innovation process within a city, the expanded market access may further incentivize firms to find market niches of new products and services more easily (Garrison and Souleyrette II, 1994, 1996). Similarly, by increasing the speed of commuting trips, transportation improvements may also ease access to skilled labors within a city as well as extend spatial borders of labor markets outside of cities (Andersson and

Karlsson, 2004). Both benefits mean that firms' costs of searching for talents with knowledges and skills required for production and innovation process are reduced.

By increasing the circulation of people, transportation improvements may also facilitate knowledge diffusion and spillover at different spatial scales. When inter-city (or inter-region) transport costs are relatively high, knowledge production and diffusion are likely to be confined by a time distance threshold such as workers' daily commuting (Andersson and Karlsson, 2004). Improvements of transport infrastructure such as highways or HSR reduce the costs of human interactions across cities, thus speeding up the communication and sharing of knowledge and ideas (Dong et al., 2020; Gao and Zheng, 2020). Dong et al. (2020) suggests two channels through which transportation improvements impacts inter-city knowledge diffusion. First, increased inter-city circulation of population would not only allow better matching among high skilled workers cities along the transportation network to form new research teams, but also enhance the collaborations among existing research teams working at the inter-city level (Dong et al., 2020). Second, high-skilled workers who originally reside in large cities may migrate to small ones that have good connections to the large cities to enjoy the lower living costs there while being able to easily meet and interact with their cohorts at large cities, thus increasing the aggregate productivity and human capital in the connected small cities (Dong et al., 2020). Agrawal et al. (2017), on the other hand, suggest that road improvements may also contribute to innovation by intensifying the intra-city knowledge flows even without attracting new labors into a city.

As a new mode of transportation, HSR generates economic effects that have some distinct features. First, unlike highways or conventional railways (CR) with frequent station stops, HSR introduces "discontinuous" spatial impacts (Vickerman, 2015). It not only widens the gaps between HSR and non-HSR cities, but also generates differential impacts across the cities connected by it (Ureña et al., 2009; Garmendia et al., 2012). While higher-orders (larger) cities may benefit from expanded access to various resources such as capital, labor, and services and enlarged markets through HSR network, lower-order (smaller) cities are likely to be further peripheralized as HSR facilitates the outflows of labor, capital, and other resources from those cities into larger cities, which may weaken their own innovation capacity (Hall, 2009; Garmendia et al., 2012; Yin et al., 2015). Second, mainly serving the transport of passengers, HSR does not generate equal effects across industries but favors those sectors that are sensitive to human interactions and knowledge exchange, such as business services and advanced manufacturing sectors (Cheng et al., 2015, Shao et al., 2017, Wang et al., 2020).

2.3 Urban economic impacts of HSR in China

Empirical studies of the HSR effects in China mostly focus on the direct impacts of HSR investment on transport accessibility or travel time (e.g., Yang et al., 2018) and the wider economic impacts such as the overall urban productivity, population, and economic growth (e.g., Cheng et al., 2015; Liu and Zhang, 2018; Jiao et al., 2020; Li et al., 2020; Dong et al., 2021; Ma and Liu, 2021), urban spatial structure (e.g., Wang et al., 2019), urban land use growth (Pan et al., 2020), or industrial evolution (Zhu et al., 2019; Xiao and Lin, 2021). While the catalyst role of HSR in promoting overall urban growth is usually found, results on the HSR effects on industrial structure are still disputed. For example, Zhu et al. (2019) found that better HSR accessibility increases the chances of a city to introduce new industries that are less related to existing industrial base and render the industrial evolution pattern to be more path-breaking. Focusing on high-tech sectors, Xiao and Lin (2021) instead found that HSR has resulted in the introduction of high-tech firms in a ctiy to be more depenent on the city's existing industrial base. Direct empirical evidence on the impacts of HSR networks on innovation and knowledge production are relatively few (e.g., Gao and

Zheng, 2020, Dong et al., 2020, Wang et al., 2020) and mostly focus on the overall innovation performance (e.g., Cheng and Liu, 2015). These indicate that the role of HSR in facilitating the growth and innovation of knowledge- or tech-intensive sectors in China deserves to be further explored. Moreover, the relationship between HSR investment and sources of agglomeration economies—the intermediate stage of HSR's economic effects—are not explicitly examined in empirical studies. This study contributes to the studies on urban innovation and HSR's economic benefits in China by filling these gaps.

3. Research Design

This study uses the EI industry as an example to explore the innovation benefits of HSR investments in China. The EI industry is chosen because it is usually considered as a tech-intensive sector and thus more likely to be sensitive to the transport costs of passengers. The industry was put as one of the 10 pillar industries according to the 12th Five-Year Plan of China and took 1/4 to 1/3 of the invention patents in recent years (Fudan Institute of Industrial Development et al., 2017, Meng and Li, 2002). Based on the literature review, the following hypotheses are tested:

Hypothesis 1: Both at the intra-city (local) and inter-city (non-local) access to various innovation factors including knowledge sources (e.g., universities/research institutions), specialized labors, producer service suppliers, and consumer markets (through HSR network) matter in the innovation performance of the EI sector across Chinese cities.

Hypothesis 2: Large cities are more likely to benefit from inter-city agglomeration spillover effects (through HSR network) than small cities in terms of innovation outcomes of the EI sector.

3.1 Conceptual model

This study follows knowledge production function (KPF) approach initiated by (Griliches, 1979). Cities are used as the basic units of analysis in the KPF to model the relationships between innovation inputs and outputs (Acs et al., 2002b, Moreno et al., 2005). Specifically, innovation outputs (**I**) of the EI sectors in city *i* is modelled a function of research and development (R&D) input levels (**R**) and a vector of factors (**Z**) that potentially facilitates knowledge production and exchange:

$$I = R^{\alpha} \cdot Z^{\beta} \cdot e \qquad (1)$$

where e is a random independent and identically distributed error term.

Deriving from studies of agglomeration economies as well as the innovation system (Fischer, 2001), this study identify the following categories of key factors (**Z** variables) (see Figure 1): (1) production sectors, which are the central actors in the innovation system; (2) scientific sectors, which include universities and research institutions specialized in science and engineering disciplines as well as workers specialized in science and technical service sectors; (3) producer service sectors, which provide financial, legal, or marketing assistance for firms' innovation process; (4) customer markets; (5) institution/policy sectors, which facilitate the informal or formalized linkages between actors in an innovation system. Factors (1)-(4) capture different sources of agglomeration economies including access to competitors and professional service suppliers (input sharing, knowledge spillover), scientific or other specialized workers and universities/research institutions (labor marketing pooling, knowledge spillover), and final customers (market access). To test the hypotheses, different agglomeration economies are measured at both intra-city and inter-city scales. Given that HSR mainly facilitates passenger flows, this study mainly looks at 4 sources of inter-city agglomeration economies (related with Factors (2)-(4)) that are mostly linked to opportunities of human interactions (see Figure 1).

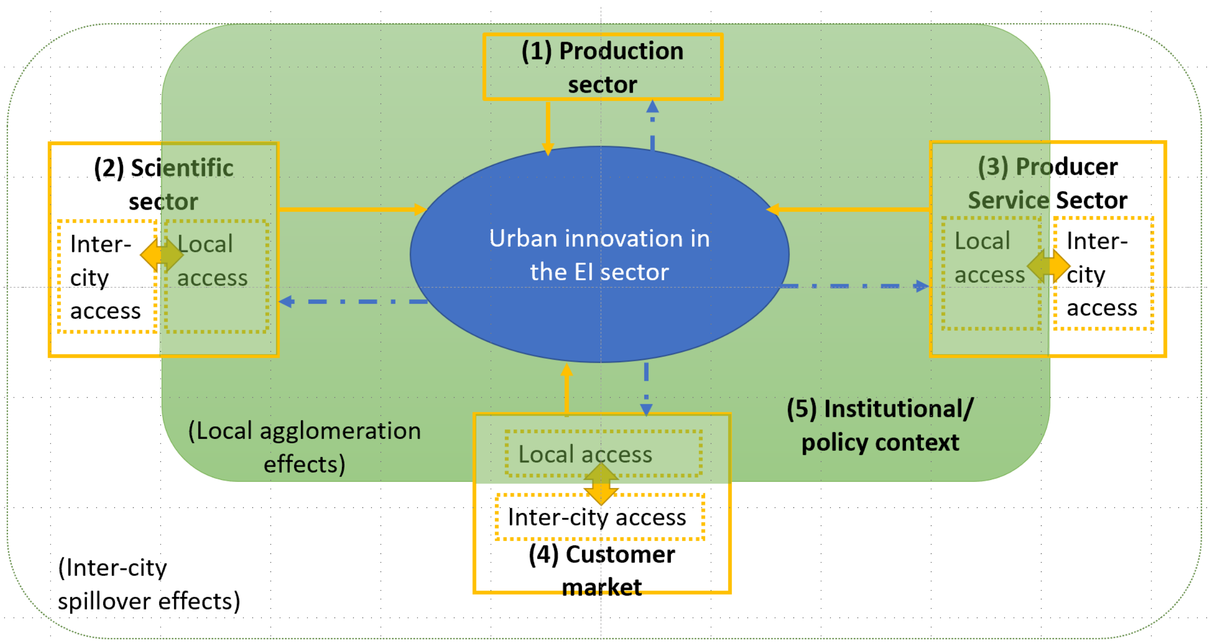

Figure 1 Conceptual framework of urban innovation*

*Extended from the the Regional Innovation System framework by Fischer (2001)

Following previous studies (e.g., Melo et al., 2009; Graham and Melo, 2011), the 3 sources of inter-city agglomeration economies are operationalized by transport accessibility measures. Transport accessibility is a term that accounts for the availability of opportunities of interactions across space as well as the transport costs for accessing those opportunities (Andersson and Karlsson, 2004; Yang et al., 2018). To reflect the role of HSR network, this study applies gravity-type transport accessibility indices, with the train time mainly through the HSR network used for discounting the travel impedance between cities (see detailed discussions in Section 3.4.2).

In addition to the inter-city accessibility effects, this study also tests whether there are additional innovation benefits associated with being close to HSR stations. Previous studies indicate that economic activities are likely to be concentrated near the inter-regional transport infrastructure such as HSR stations (e.g., Pan et al., 2020) or highways (e.g., Holl, 2004), which may potentially generate more urban growth and ultimately innovation.

3.2 Differential effects of accessibility by city size

To test how the effects of inter-city accessibility by HSR vary by city size, a categorical variable approach is applied here. Using the natural log form of innovation outputs for a city (i) and differentiating between local and non-local effects of innovation factors, equation (1) is modified as:

$$lnI_i = C + \alpha R_i + \sum_g \beta_g Z\_local_i + \sum_j \beta_{j1} CitySize_{ij} + \sum_m \beta_m Z\_Acc_i + \sum_j \beta_{j2}(CitySize_{ij} * Z\_Acc_i) + \varepsilon_i \quad (2)$$

where Z_local_i represents g number of the local determinants of innovation for city i; $CitySize_{ij}$ are the dummy variables representing the size category ("j") of city i; Z_Acc_i represents a vector of transport accessibility variables; $CitySize_{ij} * Z\_Acc_i$ are interactive terms capturing the variations of accessibility effects by city size classes; ε_i is the random error term.

3.3 Endogeneity and instrumental variables

Previous studies have emphasized the possible endogeneity between HSR investments and urban growth (Chen and Haynes, 2015; Li et al. 2020; Pan et al., 2020; Zhang et al. 2020). For example, it is likely that the construction and planning of HSR network in China favor those cities with high innovation capacities. Furthermore, there might be unobserved and persistent factors that affect both HSR investment and urban innovation. To deal with the potential endogeneity issue, instrumental variables are employed to control for the potential bias due to the endogeneity of HSR investments.

Instruments are expected to be associated with changes in inter-city accessibility by HSR or proximity to HSR stations but do not directly lead to changes in urban innovation. The first type of instrument variables is constructed based on the courier routes and stations in the Ming Dynasty of China (1368 – 1644 AD). The *courier_q4* instruments are dummy variables representing the four quintiles of the number of courier stations each city hosted during the Ming Dynasty. The *Acc_courier* instruments are defined as follows:

$$Acc\_Courier_i = \sum_{j \neq i} Courier_j / Dist\_routes_{ij}\ ,\ \ Dist\_routes_{ij} \leq Dist_{threshold} \qquad (3)$$

where $Courier_j$ represents the number of courier stations in city j, $Dist\_routes_{ij}$ represents the shortest distance between city i and j along courier routes of the Ming Dynasty, and $Dist_{threshold}$ is the maximum distance defined in consistent with the travel time thresholds of the inter-city accessibility variables (see discussions in Section 3.4.2). Data on historical couriers are obtained from the CHGIS Dataverse of Harvard University (Berman and Zhang 2017). Constructed based on historical data of more than 370 years ago, these instruments can be reasonably considered as exogenous to urban innovation at present.

The second type of instrumental variables are constructed based on the geomorphological characteristics surrounding cities. The *geomtype* instruments are defined by the ratio of land area for a particular type of landform to the total land area within a certain distance buffer of each city. The distance thresholds are defined in the same way as those in equation (3). Data on geomorphology are obtained from China's National Catalogue Service For Geographic Information (www.webmap.cn). The area shares of different landform types surrounding cities are combined to avoid the high correlation between the measures. Based on the preliminary examination of the correlation between the *geomtype* instruments and the endogenous variables (i.e., proximity to HSR stations, inter-city accessibility measures), the final model use 4 *geomtype* instruments (see Appendix I for detailed definitions). It is intuitively obvious that landforms do influence the difficulty of HSR construction but do not directly relate to urban innovation. In addition, interaction terms between *courier_q4* and *geomtype* variables are used as instruments for $CitySize_{ij} * Z\_Acc_i$ variables in Equation (2).

3.4 Data and variables

The study areas include 75 prefectural-level or above cities that were supported to be built as innovative pilot cities since 2008 (see Figure 2). These cities include the 4 municipalities, 27 provincial capital cities, and 44 other cities from 17 provinces of China[1]. The chosen pilot cities were prioritized to receive multiple levels of resources and policy supports from China's Ministry of Science and Technology and National Development and Reform Commission in terms of, for example, creating innovative policy environments, cultivating, and introducing talents through

[1] The list of innovative pilot cities and the starting years of each city being approved as a pilot city is derived from: https://www.now168.com/article/20180804/2968.html

funding major projects, and constructing key innovation bases in those cities (Zhang, 2015). Compared with most of other non-pilot cities, the innovative pilot cities are on average more economically and politically advantaged; they are more likely to share similar economic background and institutional/policy environment to promote innovation activities, thus minimizing the unobserved heterogeneity effects.

Using the 2015 population statistics, the 75 study areas are categorized into 4 classes referring to the criteria by the State Council of China: small and medium sized cities (population in 0.2-1 million), Type-II large cities (population in 1-3 million), Type-I large cities (population in 3-5 million), and mega-cities (population larger than 5 million).

Based on the definition by China's Ministry of Industry and Information Technology, the EI sectors are defined as composed of EI manufacturing and Software and Information Technology (IT) service sectors. The EI manufacturing sectors refers to the "Computer, Communications, and other Electronic Equipment Manufacturing" industry in the framework of Industrial Classification for National Economic Activities released by the National Statistical Bureau of China[2]. This definition matches the definition by China's Intellectual Property Bureau. The EI service sector refers to the Information Transmission, Computer Service and Software industry in China's Industrial Classification.

Innovation performance across cities is measured by patent data. Though patent statistics are usually considered as intermediate instead of final outputs of innovation (Griliches, 1979, Hall et al., 2001), they are considered as good indicators of examining new technological knowledge creation (Acs et al., 2002a, Wong et al., 2018) as the codified part of technological knowledge has been recorded (Wong et al., 2018). Patent data for the 75 pilot cities Chinese cities were queried from the Patent Information Service Platform (PISP) (http://chinaip.sipo.gov.cn/) for the 2016-2018 period. Invention patents are fundamental to the urban economy in the long run (Sun, 2000). This study thus uses invention patents to represent urban innovation outcomes and apply the natural log form, "ln(invention +1)" (Wang et al., 2020), to run KPF models for urban innovation outputs. The three-year average of invention patent counts for each city are used to eliminate possible variations of market conditions within each city over the study period.

The 3rd National Economic Census National Economic Census data (2013) is used to construct the R&D inputs and all measures related with employment statistics[3]. The 2015 China City Statistical Yearbook and China City Construction Statistical Yearbook are used to retrieve other socio-demographic and infrastructure statistics for constructing the other city-level variables. Using the lagged form of the above explanatory variables reduce the possible reverse causality issue: urban factors such as agglomeration externalities and environment measures in the past years (prior to 2016) is correlated with factors in the present year (2016-2018), but not caused by innovation outcomes in the present year.

3.4.1 Measures of key factors of innovation at the city-wide level

R&D inputs are a key component of the KPF and are measured as the R&D expenditure in the EI sector divided by the total number of employees in the sector aggregated at the city level (*R&DperEmp*). Urbanization economies are measured by the total population size categories of each city (*CitySize*). Localization economies are measured by the percentage of each city's employment in

[2] Source: http://www.stats.gov.cn/tjsj/tjbz/hyflbz/

[3] The National Economic Census of China are conducted by the National Statistics Bureau of China every 4-5 years.

the EI production and service sectors (*EIEmp*). Local competition of firms is measured as the number of employees in the EI manufacturing and service sectors divided by the number of EI firms of a city (*AvgSize*). The level of industrial diversity of each city (*DIVINX*) is measured by the Herfindahl-Hirschman Index:

$$DIVINX_i = \sum_{j=1}^{18} s_{ij}^2$$

where s_{ij} is the employment share of industry j for city *i*. The 18 main categories of non-agricultural industries defined by China's National Bureau of Statistics are used in the construction of HHI. A lower value of $DIVINX$ means a more diversified industrial structure for a city.

The scientific sector in the urban innovation system is measured by two variables: universities/research institutions (*Univ*) and workers specialized in science sectors (*SciTech*). Using the results of the 3rd round of national subject evaluation (2012) conducted by China's Ministry of Education[4], the *Univ* variable is constructed as the number of universities and research institutions which received more than 75 scores in science/engineering disciplines of each city divided by the city's total urban population. Local specialized workers (*SciTech*) are measured by the share of employees in Scientific Research and Technical Service sectors of a city. Similarly, the producer service sector (*ProdSrv*) is measured by the employment share of Finance, Real Estate, and Leasing and Business Services sectors of each city. Local customer markets for the EI sector (*ICTUser*) are defined as the total number of subscribers of ICT products (i.e., broadband, telephone, and mobile devices) divided by the total population of each city in 2015.

The institutional/policy environment of a city is proxied by the number of years a city has been approved to be an innovative pilot city until 2019 (*PilotYrs*) [5]. For example, Shenzhen is the first approved innovative pilot city in 2008 and is assigned a value of 11 for the *PilotYrs* variable. The earlier a city is approved as an innovative pilot city, the longer years of national supports for innovative activities it may receive, and the higher level of its innovation outputs is expected.

3.4.2 Measures of inter-city agglomeration economies

The gravity-based accessibility measure (Hansen, 1959) is used here to combine the influence of transport costs and spillovers of agglomeration effects from other cities (Holl, 2004; Melo et al., 2009). A city *i*'s access to key innovation factors outside of its boundary, including universities/research institutions (*Univ*), science/technical workers (*SciTech*), producer services (*ProdSrv*) and final customers (*ICTUser*) of other cities is expressed as follows:

$$AccUniv_i = \sum_{j \neq i} Univ_j / T_{ij}\,, \qquad T_{ij} \leq T_{threshold}$$

$$AccSciTech_i = \sum_{j \neq i} SciTech_j / T_{ij}\,, \qquad T_{ij} \leq T_{threshold}$$

$$AccProdSrv_i = \sum_{j \neq i} ProdSrv_j / T_{ij}\,, \qquad T_{ij} \leq T_{threshold}$$

[4] Source: http://www.cdgdc.edu.cn/xwyyjsjyxx/xxsbdxz/index.shtml
[5] Source: https://www.now168.com/article/20180804/2968.html

$$AccICTUser_i = \sum_{j \neq i} ICTUser_j / T_{ij}\,, \qquad T_{ij} \leq T_{threshold}$$

where T_{ij} is the train time between cities i and j mainly through the HSR network.

The GIS data of China's High-Speed Railway Stops and Network (2016) are queried from the open data source of Harvard World Map Repository (see Figure 2). The dataset contains the geographic (e.g., length, location) and other information (e.g., Chinese names, the range of maximum speed (km/h), conditions) of China's HSR links/nodes as of 2016 (Li, 2016). The travel time for each HSR network segment is calculated as the ratio of the length and the lower bound of the maximum speed range of the railway line. In this way, we assume that HSR operates in a normal condition without constant interruptions or accidents, which is reasonable given the high reliability of HSR operation in China after 2015. The inter-station travel time through HSR between is then estimated as the shortest-path travel time on the HSR networks. The medium train time of all pairs of train stations within the boundaries of respective origin and destination cities are used as the inter-city HSR travel time. However, cities without HSR stations may also experience increased inter-city accessibility from HSR investments (e.g., Yang et al., 2018). To include those cities not accommodating a HSR station (as of 2016), we assume that persons travel from a conventional railway (CR) station located closest to the centroid of their home city to the nearest HSR train station connected by CR network (or vice versa). The travel speed on the CR network between the chosen CR station and the nearest HSR train station is set as 100 kilometers per hour (as of 2015). Data on China's network lines and stations in 2015 is queried and compiled from open data sources of China's National Catalogue Service For Geographic Information (www.webmap.cn) and Open Street Map. Table 1 indicates the summary statistics of the estimated inter-city train time.

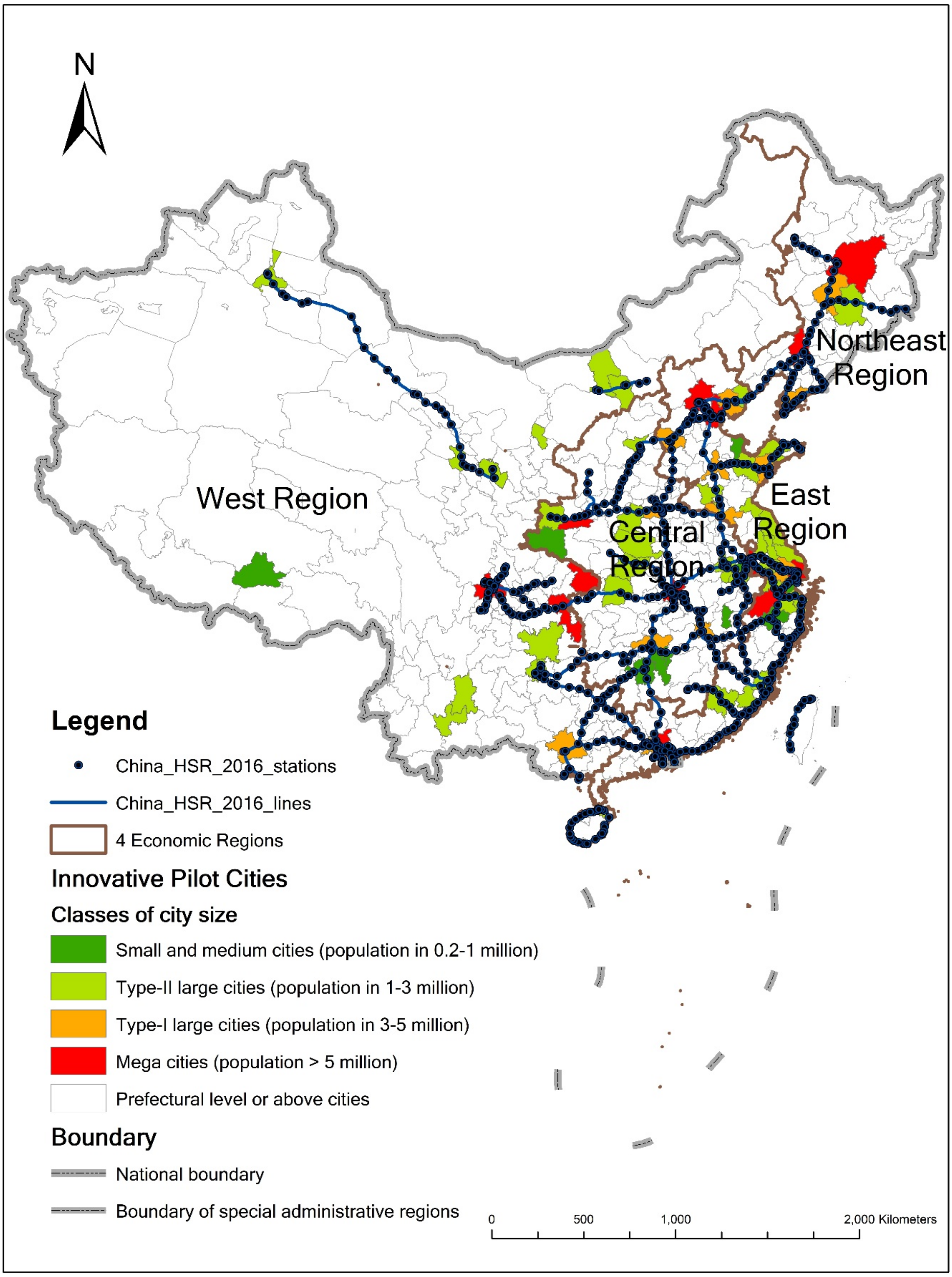

Figure 2 75 prefectural-level or above innovative pilot cities and HSR networks in mainland China*

***National boundary of China and boundaries of prefectural level or above administrative units in China are obtained from China's National Catalogue Service For Geographic Information (www.webmap.cn), using the 1:1 million national basic geographic database of 2020**

Table 1 Summary Statistics of rail network travel time between pairs of cities designated as innovative pilot cities at origin or destinations (hours)

	min	p5	p10	p25	p50	p90	p95	max
Excluding cities not having a HSR train station (HSR travel time)	0.17	1.24	2.07	3.64	5.44	9.97	11.27	15.82
All cities (mixed HSR-conventional rail travel time)	1.43	1.71	2.67	4.77	7.03	11.20	19.78	42.23

The inter-city train time thresholds are set as 2, 3.6, and 4.8 hours, which correspond to the 10th and 25th percentile train time estimated based on the HSR networks and the 25th percentile train time estimated based on the mixed HSR and CR network, respectively. The 2-hour travel time is the maximum threshold where HSR travel is expected to be more advantageous than air travel (Ureña et al., 2009). Using the average lower-bound speed of HSR lines in China (265 km/h as of 2016), the 3.6-hour time distance threshold approximates 1000-kilometer distance threshold below which HSR travel remains competitive to air travel (Ureña et al., 2009). The 4.8-hour time threshold approximates the estimated HSR train time between Beijing and Shanghai (5 hours as of 2016), the two core cities in China. This time threshold is chosen to ensure that the catchment areas of the two core cities via HSR networks do not overlap each other. The three inter-city travel time thresholds are used to construct the 4 types of accessibility variables and the corresponding interaction terms, which are then included separately in the regression analyses due to the concerns of multi-collinearity. The correlation between inter-city accessibility variables and local agglomeration measures are also checked and the highest correlation coefficient is less than 0.5, suggesting that the two types of variables measure agglomeration economies at different spatial scales. Using the same average speed of HSR lines (265 km/h), the distance thresholds for constructing the *Acc_courier* and *geomtype* instruments for inter-city accessibility variables measured at the 2-hour, 3.6-hour, and 4.8-hour train time thresholds are defined as 530-km, 954-km, and 1272-km respectively.

3.4.3 Measures of proximity to HSR station

The additional location advantages of being close to HSR stations are measured by 3 dummy variables representing whether a city has at least one HSR station within 10 km (*proxHSR_10km*), 10-20 km (*proxHSR_10_20km*), or beyond 20 km (*nonproxHSR*, reference category) of its (geometric) center, respectively. The HSR station proximity variable and inter-city accessibility variables have a weak correlation of around 0.38, showing that the two types of measures capture HSR-based accessibility at different spatial scales.

3.4.4 Control variables

Dummy variables representing the economic region a city is located (*EconRgn*) are included in the model to control for the unobserved regional-level heterogeneity effects. Four economic zones—East, West, Central and Northeast regions defined by the Statistic Bureau of China[6] are used here (see Figure 2). The four regions vary significantly in terms of socio-economic development levels and HSR investments. The East region is used as the reference group in the regression analyses because takes the largest share of HSR length and stations in China (Wang et al., 2020). The region also has

[6] Source: http://www.stats.gov.cn/ztjc/zthd/sjtjr/dejtjkfr/tjkp/201106/t20110613_71947.htm

the largest gains in inter-city transport accessibility thanks to the introduction of HSR network in China after 2008 (Yang et al., 2018).

The level of foreign direct investments (FDI) is expected to have a positive relationship with urban innovation. Here the FDI intensity ratio — the total FDI in a city normalized by the gross domestic product (GDP) of the city in the same year (2015) — are used in the regression model to facilitate the comparison of results between cities of different economic scales. Urban amenity may also contribute positively to innovation by attracting high-human capital workers (Giuliano et al, 2019) and is represented by the percentage of green covered area in the total built up areas of a city (*GreenCov*). Finally, the urban road network density (*RdNwDen*) is used to represent the intra-urban transport accessibility, which is expected to positively influence urban innovation by promoting economic efficiency (e.g., Yao et al., 2022) and facilitating human interactions within a city (e.g., Andersson and Karlsson, 2004; Agrawal et al, 2017).

Table 2 shows the definition and descriptive statistics of all variables.

Table 2 Definition and summary statistics of dependent and independent variables (N=75)

Variable	Description	Statistics			
Dependent variables		Mean	Std. Dev.	min	max
lnInvnt	Natural log of (invention patent +1) (invention = 3 year averages of invention patent counts in 2016-2018)	5.69	1.87	1.67	10.22
Independent variables					
CitySize	City size classification (based on population within districts under the jurisdiction of a city in 2015)	Freq.	Percent		
Small and medium sized cities	Population in 200,000 and 1 million	10	13.33		
Type II large cities	Population in 1-3 million	39	52		
Type I large cities	Population in 3-5 million	14	18.67		
Mega cities	Population larger than 5 million	12	16		
EconRgn	The 4 economic zones	Freq.	Percent		
East region		37	49.33		
Central region		16	21.33		
West region		17	22.67		
North-east region		5	6.67		
Key factors of innovation at the city-wide level		Mean	Std. Dev.	min	max
R&DperEmp	Total R&D expenditure in the EI sector/Total employees in the EI sector (10,000 RMB/person, 2013)	0.63	0.68	0	3.39
TotEmpDen	Overall employment density of a city (Number of employees per square kilometre, 2013)	370.26	652.80	6.31	4858.99
EIEmp	Share of employment in the EI sector in the total employment (2013)	0.04	0.04	0	0.21
DIVINX	Industrial diversity of a city measured by Herfindahl index (HHI) (value range: [1/18, 1], 2013)	0.21	0.10	0.08	0.61
AvgSize	The average size of firms in the EI sector (Number of employees/Number of firms, 2013)	48.60	29.06	16.03	149.53

Table 2 (Continued. 1)

Variable	Description	Statistics			
Key factors of innovation at the city-wide level		Mean	Std. Dev.	min	max
Univ_pop	Number of universities/research institutions specialized in science and engineering disciplines (scored A- or above)/Population	0.003	0.004	0	0.02
SciTech	Percent of employment in science and technical service sector in the total employment (2013)	0.02	0.01	0.01	0.09
ProdSrv	Percent of employment in producer service sector in the total employment (2013)	0.08	0.04	0.03	0.27
ICTUser	Subscribers of ICT devices, including telephones, mobile phones, and broadband /Total population (%, 2015)	2.19	1.53	0.76	10.11
PilotYrs	Number of years approved as innovative pilot city (until 2018)	7.41	3.30	2	12
Other urban environment factors		Mean	Std. Dev.	min	max
FDI_GDP	Total FDI/ Gross Domestic Product (GRP) of a city (10,000 USD/10,000 RMB, 2015)	0.02	0.02	0	0.11
GreenCov	Green covered area as of percentage of land area in built district (%, 2015)	41.20	5.16	26.57	61.58
RdNwDen	Density of road network in built district (kilometer/square kilometer)	6.22	2.48	0.32	14.57
Proximity to HSR stations		Freq.	Percent		
proxHSR_10km	Distance from city center to the nearest HSR station <10 km	15	20		
proxHSR_10_20km	Distance from city center to the nearest HSR station in 10-20 km	17	22.67		
nonproxHSR	Distance from city center to the nearest HSR station >20 km	43	57.33		
Inter-city accessibility measures based on HSR		Mean	Std. Dev.	Min	Max
AccUniv_2h	Using a 2-hour time threshold	10.09	12.85	0	51.57

Table 2 (Continued.2)

Variable	Description	Statistics			
Inter-city accessibility measures based on HSR		Mean	Std. Dev.	min	max
AccUniv_3.6h	Using a 3.6-hour time threshold	14.02	14.51	0	56.17
AccUniv_4.8h	Using a 4.8-hour time threshold	17.33	15.64	0	62.54
AccSciTech_2h	Using a 2-hour time threshold	583119.1	596633.3	0	2356995
AccSciTech_3.6h	Using a 3.6-hour time threshold	851744.2	730468.8	0	2606586
AccSciTech_4.8h	Using a 4.8-hour time threshold	1067893	828287.6	0	2854792
AccProdSrv_2h	Using a 2-hour time threshold	2085138	2315475	0	9752173
AccProdSrv_3.6h	Using a 3.6-hour time threshold	2953073	2610487	0	10500000
AccProdSrv_4.8h	Using a 4.8-hour time threshold	3639071	2871103	0	11200000
AccICTUser_2h	Using a 2-hour time threshold	11702.12	10002.35	0	38652.51
AccICTUser_3.6h	Using a 3.6-hour time threshold	17151.98	12793.8	0	44569.75
AccICTUser_4.8h	Using a 4.8-hour time threshold	21318.89	14745.66	0	49663.67

4. Results and discussions

This section discusses the regression results of urban innovation outputs in the EI sector. We examined the correlation coefficients between pairs of explanatory variables and experimented with different specifications to avoid the multicollinearity issue. The final model includes a set of variables that are not closely correlated with each other while being able to address different dimensions of innovation factors as defined in the conceptual model. The city size categorical variables as the measure of urbanization economies are also used as surrogates for the local market size of ICT device consumers (*ICTUser*). The per capita number of universities/research institutions with top rankings in science and engineering disciplines in a city (*Univ*) is positively related with the share of science and technology workers (*SciTech*) and is used in the model to represent the city-level scientific sector.

The OLS and generalized methods of moments (GMM) estimators are used to estimate the determinants of innovation outcomes. The OLS models are conducted in preliminary tests[7]. The adjusted R-square for all models are around 0.85 - 0.87, indicating that the sets of explanatory variables explain most of the variations in urban innovation in the EI sector across the study areas. We also run Moran's I tests for spatial correlation among the residuals (Moran, 1950), with the spatial weight matrix defined by the inverse distance between the cities. The results indicate that the values of Moran's I for residuals of all regression models do not significantly differ from 0. This

[7] Results using OLS are not reported but are available upon request.

implies that the spatial spillover effects across neighboring cities have been absorbed by the accessibility variables in the model.

The Hansen J statistic (1982) are used to test the validity of GMM model (including the validity of instrumental variables and the overidentification restrictions) (Baum, 2006). Results indicate that the null hypothesis that all instruments are uncorrelated with the error terms cannot be rejected in all models, suggesting that the validity of the final models (see Table 3). The GMM C statistics are used to test for the endogeneity of inter-city accessibility and HSR station proximity variables (Baum, et al., 2003, Baum, 2006). Results indicate that the null hypothesis of their exogeneity is only weakly rejected (at p<0.1 level) when *AccSciTech_4.8h* is used as the inter-city accessibility variable in the regression model. Considering the potential endogeneity issue, instrumental variables are used for all models. The following discussions uses results using GMM with heteroskedastic errors and instruments (IV-GMM) and focus on those significant explanatory variables (p<0.1). The asymptotic T-test statistics (Allison, 1999) are applied to examine if there exist significant differences in the estimated coefficients for the same independent variable across different model specifications. The results indicate that none of the T-test statistics are significant (results not shown).

Table 3 Results for urban innovation in the EI sector (N=75) [a]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
R&DperEmp	0.562***	0.502***	0.514***	0.503***	0.518***	0.503***	0.549***	0.552***	0.572***	0.534***	0.518***	0.544***
	(4.12)	(6.55)	(4.32)	(6.17)	(6.69)	(4.49)	(7.09)	(4.49)	(5.50)	(6.90)	(4.10)	(5.24)
CitySize (reference group: mega cities)												
Small and medium sized cities	-3.159***	-3.624***	-3.249***	-3.348***	-4.248***	-3.485***	-3.237***	-3.493***	-3.389***	-3.306***	-3.978***	-3.474***
	(-5.08)	(-5.25)	(-3.85)	(-5.11)	(-5.76)	(-4.71)	(-4.89)	(-4.46)	(-4.39)	(-4.54)	(-3.90)	(-4.35)
Type II large cities	-2.532***	-2.651***	-2.536***	-2.779***	-3.020***	-2.827***	-2.432***	-2.843***	-2.571***	-2.569***	-3.218***	-2.764***
	(-7.45)	(-8.11)	(-7.49)	(-6.29)	(-7.19)	(-6.49)	(-6.42)	(-5.59)	(-6.71)	(-5.69)	(-4.56)	(-5.86)
Type I large cities	-1.060*	-0.958*	-1.053*	-1.258*	-1.173*	-1.246*	-1.075*	-1.347*	-1.101*	-1.03	-1.494*	-1.134*
	(-2.13)	(-2.46)	(-2.10)	(-2.13)	(-2.24)	(-2.18)	(-2.22)	(-2.22)	(-2.23)	(-1.89)	(-1.99)	(-2.14)
Key local agglomeration factors												
EIEmp	8.221*	11.81***	9.394**	6.706*	10.52***	8.743***	6.739	9.436***	8.810**	7.172*	10.07***	9.384***
	(2.53)	(4.65)	(3.05)	(2.00)	(4.98)	(3.39)	(1.85)	(3.53)	(3.07)	(2.23)	(3.92)	(3.57)
DIVINX	6.726***	3.465*	4.973**	7.314***	3.634**	4.908**	6.108**	5.009***	4.865**	7.061***	4.548***	5.122***
	(3.70)	(2.55)	(3.01)	(3.51)	(2.72)	(3.06)	(2.91)	(3.30)	(3.02)	(3.72)	(3.34)	(3.42)
Univ_pop	146.2***	111.1***	142.2***	154.4***	130.8***	145.7***	155.2***	121.1***	157.3***	157.0***	122.2***	158.7***
	(5.05)	(3.54)	(5.11)	(5.50)	(4.80)	(5.57)	(5.85)	(4.10)	(6.11)	(5.88)	(3.83)	(5.78)
ProdSrv	9.577**	4.268*	7.066**	10.35***	6.811**	7.801***	9.859***	6.872**	7.843**	10.21***	5.913*	7.418**
	(3.18)	(1.97)	(2.98)	(3.56)	(2.87)	(3.34)	(3.60)	(2.72)	(3.25)	(3.70)	(2.40)	(3.19)
Inter-city accessibility												
	Acc_Univ			Acc_SciTech			Acc_ProdSrv			Acc_ICTUser		
	2h	3.6h	4.8h	2h	3.6h	4.8h	2h	3.6h	4.8h	2h	3.6h	4.8h
All groups	-0.0129	-0.0413	-0.035	9.76E-08	-1.09E-06*	-7.00E-07	5.10E-09	-1.10E-07	-1.50E-07	-1.00E-06	-3.00E-05	-3.00E-05
	(-0.41)	(-1.37)	(-1.54)	-0.15	(-2.15)	(-1.65)	-0.03	(-0.74)	(-1.43)	(-0.04)	(-0.95)	(-1.50)
Small and medium sized cities	-0.0165	0.0466	0.0347	-8.10E-07	1.00E-06	7.00E-07	-9.80E-08	8.59E-08	1.60E-07	-3.00E-05	3.00E-05	3.00E-05
	(-0.30)	-1.02	-0.79	(-0.65)	-1.73	-0.9	(-0.31)	-0.45	-0.87	(-0.48)	-0.74	-0.84
Type II large cities	0.0352	0.0693*	0.0624*	3.90E-07	1.6E-06**	1.26E-06*	1.8E-07	2.75E-07	2.97E-07*	3.89E-05	6.38E-05	5.68E-05*

Table 3 (Continued.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	(1.00)	(2.05)	(2.21)	(0.52)	(2.78)	(2.32)	(0.96)	(1.79)	(2.37)	(0.99)	(1.90)	(2.27)
Type I large cities	-0.0184	-0.00132	0.0234	-5.10E-07	4.00E-07	5.00E-07	2.77E-09	-8.15E-08	1.30E-07	-2.00E-05	-5.00E-06	2.00E-05
	(-0.52)	(-0.04)	-0.73	(-0.82)	-0.66	-0.95	-0.02	(-0.54)	-0.95	(-0.50)	(-0.15)	-0.85
Other Urban environment factors												
FDI_GDP	17.77**	13.08*	16.65**	14.22**	14.29**	16.88***	13.83**	9.229*	15.14***	14.38**	8.47	15.42***
	(2.62)	(2.13)	(3.04)	(2.64)	(2.88)	(3.40)	(2.65)	(1.99)	(3.45)	(2.89)	(1.78)	(3.59)
GreenCov	0.0416**	0.0332	0.0398*	0.0438**	0.0371	0.0381*	0.0407**	0.0377*	0.0334*	0.0437***	0.0396*	0.0382*
	(3.15)	(1.67)	(1.99)	(3.20)	(1.66)	(2.47)	(3.04)	(2.25)	(1.97)	(3.35)	(2.57)	(2.55)
_cons	3.294**	3.570**	3.642**	3.528**	3.765**	3.877**	3.359**	3.668**	3.833**	3.218*	4.150**	3.815**
	(2.86)	(3.17)	(3.24)	(3.00)	(3.26)	(3.38)	(2.84)	(3.14)	(3.31)	(2.56)	(3.26)	(3.15)
adj. R-sq	0.813	0.801	0.816	0.816	0.836	0.847	0.845	0.842	0.855	0.855	0.861	0.863
J test statistics	6.859	12.356	11.19	7.36	12.435	12.429	7.791	15.146	9.296	1.22	1.65	1.53
J test statistics p value (H0=valid model)	0.81	0.338	0.428	0.769	0.332	0.332	0.732	0.176	0.595	0.2684	0.1988	0.2163

t statistics in parentheses: Underlined p<0.1; * p<0.05; ** p<0.01; *** p<0.001

a. Only results that are significant (p < 0.1) in at least one of the models are shown in the table.

4.1 R&D expenditure

Consistent with the expectations of the knowledge production function, cities with larger R&D inputs in the EI sector are found to have innovation outputs of the sector. The estimated coefficients for the *R&DperEmp* variable range from 0.5 to 0.57, suggesting that one unit increase in R&D expenditure intensity (10,000 RMB per employee) is associated with about 65 (=100*exp(0.5)-1) to 77 (=100*exp(0.57)-1) percent increase in the yearly invention patent counts in the EI sector (as of 2016-2018).

4.2 Local (city-wide) level agglomeration effects

The overall economic size of a city is also positively associated with innovation in the EI sector. The dummy variables representing the three size classes of cities all have significant and negative coefficients in all models. This means that mega cities (population larger than 5 million) have a "premium" in terms of generating innovation activities relative to cities of all other size classes, all else being equal. The estimated premiums of innovation outputs for mega cities over small and medium cities is largest, about 96-98 percent, followed by Type-II large cities (about 91-96 percent), and is smallest on Type-I large cities (about 65-78 percent). This is consistent with the theoretical expectation that cities with stronger urbanization economies have higher innovation capacity.

Localization economies, measured by the employment share of the EI sector in a city, also have positive and significant effects on urban innovation outputs of the EI sector. A 0.01-unit (1 percentage point) increase in the share of employment in the EI sector in a city is associated with 7.7-12.5 percent increase in the annual invention patent counts of the EI sector in a city during the 2016-2018 period. The positive and significant signs for the $DIVINX$ variable in all regression models indicate that the less diversified a city's industrial structure (i.e., the higher values of $DIVINX$), the higher innovation performance of the city in the EI industry. These results differ from Jacob's argument (1969) that a more diversified urban economy facilitates cross-fertilization of ideas across different industries and ultimately promotes innovation. To promote urban innovation in the EI sector, cities may need to foster employment concentration and specialization in the sector instead of pursuing a relatively balanced distribution of employment across industrial categories.

Local access to universities and research institutions received 75 or above scores in science or engineering disciplines, which is used to represent a main knowledge source for the EI sector, exhibit positive and significant effects on the innovation outputs of the sector. Local access to producer services, represented by the share of employment in the producer service sectors is also found to have positive impacts on innovation outputs of the EI sector in a city. Local competition of firms in the EI sector show no significant impacts on the innovation performance of the sector.

4.3 Inter-city agglomeration spillover effects

The effects of different sources of agglomeration economies on innovation outputs, including access to key knowledge sources (i.e., top-ranking science or engineering academic institutions), high-human capital or specialized labors (i.e., scientific/technical workers), producer service sectors--an important supplier of intermediate input for innovation, and final markets are tested at both the intra-city and the inter-city scale.

Innovation outcomes (of the EI sector) do not exhibit any association with the *AccUniv* variable measured at the 2-hour threshold train time for any type of cities. For Type-II large cities (population in 1-3 million), their innovation outputs of the EI sector are positively associated with access to top rankings science and engineering universities/research institutions in other cities through HSR network. The average marginal effects of *AccUNIV* measured based on the 3.6-hour train time threshold is about 7.1 percent, which is about 1.1 times of the marginal effects of *AccUNIV* measured based on the 4.8-hour train time threshold (see Columns (1)- (3) in Table 3).

Similarly, innovation outputs for cities of any size classes are not found to be significant associated with access to human capital of other cities within the 2-hour train time threshold. When the train time distance threshold for the inter-city access measure is extended to 3.6 hours, cities of different size classes show different responses. While the estimated coefficient for *AccSciTech* at the 3.6-hour threshold is negatively significant, the coefficients for interaction terms between *AccSciTech* and the dummy variables for small and medium sized cities and Type-II large cities are positively significant with absolute values larger than that for *AccSciTech_3.6h*. In other words, small-medium sized cities and Type-II large cities benefit from inter-city access to specialized workers and human capital within 3.6-hour time threshold in terms of innovation outputs of the EI sector; every additional 100,000 unit increase in the *AccSciTech_3.6h* variable is associated with 2.7 and 5.2 percent increase in the yearly invention counts in the two types of cities, respectively (see Columns (4)- (6) in Table 3). By contrast, innovation outputs in cities with larger than 3 million population (including Type-I large cities and mega cities) are negatively affected by *AccSciTech_3.6h* and the estimated marginal effects (with a 100,000-unit increase in the variable) is about 1 percent. The negative impacts of inter-city access to scientific and technical workers on innovation outcomes of Type-I large cities (population in 3-5 million) and mega cities (population larger than 5 million) deserves to be explored in future studies. One possible explanation is that scientists and technicians in those large cities with better access to their peers within a reasonable travel time might have a higher propensity to move out of large cities to other lower-ranked cities to enjoy lower rents and living costs while forming or maintaining collaboration with their colleagues (Dong et al., 2020), which in the long run may reduce the innovation capacity of large cities. Moreover, cities of 1-3 million population also benefit from inter-city access to scientific and technical workers at an extended train time threshold of 4.8 hours; the average marginal effects of the *AccSciTech_4.8h* variable (with a 100,000-unit increase) is about 13.4 percent, which is about 1.6 times larger than of the marginal effects of the *AccSciTech_3.6h* variable.

Type-II large cities are also the only class of cities showing positive and significant coefficients on the inter-city access to producer service workers measures based on the 3.6- and 4.8-hour train time threshold; every additional 100,000 unit increase in the two accessibility variables are associated with 2.7 and 3 percent increases in urban innovation outputs of the EI sector, respectively. However, compared with the impacts of access to science and technical workers within the 3.6-hour and 4.8-hour train time on Type-II large cities, the estimated effects of *AccProdSrv_3.6h* and *AccProdSrv_4.8h* are smaller by about 0.5 and 0.8 times, respectively.

Type-II large cities also respond positively to inter-city access to ICT device subscribes of other cities within the 3.6- and 4.8-hour train time threshold in terms of innovation outputs; the estimated marginal effects of the inter-city access measures (with a 1,000-unit increase) are 6.6 and 5.8 percent, respectively. For cities of other size class, their innovation outcomes are not significantly correlated with extended market access through HSR network.

In sum, the effects of the different sources of inter-city agglomeration economies on urban innovation are significant when the train travel time are defined beyond the 2-hour threshold and mostly accrue to Type-II large cities. These results may be explained by Wolffram's theory (2003) that transportation investment generates larger economic effects on those cities or regions where transportation infrastructure is less developed. Compared with the other three classes of cities, Type-II large cities on average have the smallest values of all the inter-city accessibility variables. This is because this city group have the largest number of cities without HSR stations (as of 2016), which resulted in elongated average train travel time to other cities and reduced inter-city accessibility for this group. However, Type-II large cities still occupies advantageous locations in China's railway network (composed of HSR and CR). Table 4 shows that compared with cities of other size classes, Type-II large cities on average have the shortest railway network distance and straight-line distance to other cities. It is expected that the introduction of HSR stations in those Type-II cities would offer new location advantages to those cities and further extend the input and output markets for them, which would further improve the innovation capacity and growth potential of those cities.

Table 4 Descriptive statistics of inter-city travel time and distance via railway network

	Small and Medium Sized cities	Type-II large cities	Type-I large cities	Mega Cities
Inter-city distance via railway network				
min	71	63	63	71
mean	574	**532**	622	558
sd	290	261	256	271
max	1055	1055	1055	1055
Inter-city train time				
min	0.2	0.2	0.3	0.2
mean	2.1	**2.2**	2.3	2.1
sd	1.0	0.9	0.9	1.0
max	3.6	3.6	3.6	3.6
Inter-city straight-line distance				
min	56	40	40	56
mean	387	**355.5**	425	397
sd	225	198	194	208
max	838	911	866	911

4.4 Other control factors

Consistent with the findings of previous studies (e.g., Chen et al., 2017, Mei & Qi, 2019), the level of FDI intensity in a city is positively associated with urban innovation in the EI sector. This implies that the more open the urban economy, the more likely that the city would have a higher innovation capacity in high-tech sectors. Cities with higher share of green spaces areas in the built-up area are also found to have higher innovation outputs of the EI sector. As discussed above, the positive impacts of urban amenities on innovation activities may be through attracting talented workers with high human capital, which play a key role in urban innovation especially in high-tech sector like EI.

Dummy variables presenting the relative location of HSR stations to cities' (geometric) centers are not found to exert significant impacts on urban innovation in the EI sector. In other words, the accessibility advantages associated with the introduction of HSR have been mostly captured by the inter-city accessibility variables and there are no specific preferences for locations near HSR stations for innovation activities in the EI sector during the study period.

The estimated coefficients on the number of years a city being approved as an innovative pilot city are not found to be significant in all the regression models. These results imply that for those cities already chosen as innovative pilot cities, the effects of policy and institutional supports on innovation activities of the EI sector over 2016-2018 are relatively homogeneous after other key factors of the innovation process have been controlled. However, future studies may be interested in further exploring the role of policy and institutional supports in innovative activities.

Finally, cities of the four economic zones are not found to differ significantly in terms of innovation outputs in the EI sector after the local urban agglomeration and environmental factors and inter-city accessibility effects have been accounted for.

5. Conclusion

This study explores the effects of HSR investment on urban innovation through different sources of agglomeration spillover effects, using the EI sector across 75 innovative pilot Chinese cities as an example. Three sources of inter-city agglomeration economies that are closely related with passenger flows are operationalized by transport accessibility variables measured at the 2-hour, 3.6-hour, and 4.8-hour train time thresholds and their differential effects across cities of different size classes are tested through a categorical variable approach. Using an IV-GMM estimator, results indicate that while local agglomeration economies exert positive impacts on innovation outputs of a city's EI sector, as expected, inter-city accessibility through HSR network mostly influence innovation outputs of Type-II large cities (population in 1-3 million). On both the production and consumption side of agglomeration economies, access to a greater pool of top science/engineering institutions and producer service suppliers, and a greater market for final demands outside of a city within train time thresholds of 3.6- and 4.8-hours exert significant impacts on innovation outputs of the EI sector for Type-II large cities but not for cities of other size classes. Considering inter-city access to high-human capital workers within the 3.6-hour train time, Type-II large cities are more sensitive to the accessibility effects in terms of innovation outcomes than small and medium-sized cities (population in 0.2-1 million). However, no additional location advantageous of proximity to HSR stations at the local level are found after accounting for the effects of inter-city accessibility by HSR.

These results add to the empirical evidence on the mechanism of HSR effects on urban innovation through extending and enhancing different sources of agglomeration economies at the inter-city scales. While the local accommodation of key agglomeration and innovation factors such as top academic institutions and producer service suppliers are important to urban innovation in the EI sector, HSR network may open up new knowledge sources, specialized labor pool, and input and output markets for cities with a population less than 3 million, which may finally enhance innovation outputs of the EI sector. The effective spatial extents of inter-city agglomeration effects may go beyond the 2-hour train time threshold of which HSR travel usually outcompetes air travel.

The results also provide some policy implications on urban innovation and HSR development in China. While cities with strong urbanization and/or localization economies may still be the future growth pole of the EI sector, non-top-tier Chinese cities, especially Type-II large cities, may also have the potential to be developed into future innovation hubs of high-tech sectors like the EI sectors if their connections to other cities endowed with knowledge sources or markets through HSR network can be further improved. To further facilitate urban innovation in China, future HSR network plan may not only emphasize the connections between higher-order cities, but also further compress the time distance and enhance inter-city accessibility between lower-order cities and high-order cities as well as among lower-order cities of different specializations at a larger spatial scale.

There are several limitations of this study. First, though IV-GMM estimators are used to cope with the endogeneity issue, this study is cross-sectional in nature and focuses on associations instead of causality. Future research may fully explore the bi-directional causation between innovation and inter-city accessibility through HSR network with the use of longitudinal data. Second, this study focuses on the EI sector, which has long been considered as a highly innovative industry and can be most sensitive to reduced costs of knowledge and human capital flows. Future research may be extended to other traditional industries that are not considered high-tech and explore whether and to what extent the introduction of HSR may bring growth and innovation benefits to those industries by compressing inter-city travel time and improving non-local knowledge and market access.

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