Intercity Innovation Collaboration and the Role of High-speed Rail Connections: Evidence from Chinese Co-patent Data

Journal:	*Regional Studies*
Manuscript ID	CRES-2021-0138.R1
Manuscript Type:	Main Section
JEL codes:	D83 - Search; Learning; Information and Knowledge; Communication; Belief; Unawarenessv < D8 - Information, Knowledge, and Uncertainty < D - Microeconomics, R41 - Transportation: Demand, Supply, and Congestion; Travel Time; Safety and Accidents; Transportation Noise < R4 - Transportation Systems < R - Urban, Rural, Regional, Real Estate, and Transportation Economics
Keywords:	Innovation Collaboration, Co-patent, High-speed Rail, Geogrpahical proximity, Institutional proximity

Abstract:	This study explores the extent to which changes in transport infrastructure counterbalance pre-existing geographic friction and foster innovation collaboration, using the Chinese HSR construction as a quasi-natural experiment. Using a comprehensive dataset of city-pair co-patents from 2005 to 2018, we show that HSR connection significantly increases inter-city co-patents, patent quality, and collaborative partnerships, and such effects are strongest for city-pairs within 250 km and decrease for longer distance. Moreover, the HSR effect is stronger for cities in similar institutional setting, indicating a negative moderating effect of institutional distance. Various robustness methods are used to confirm the validity of our findings.

SCHOLARONE™
Manuscripts

Intercity Innovation Collaboration and the Role of High-speed Rail Connections: Evidence from Chinese Co-patent Data

For Peer Review Only

Abstract

This study explores the extent to which changes in transport infrastructure counterbalance pre-existing geographic friction and foster innovation collaboration, using the Chinese HSR construction as a quasi-natural experiment. Using a comprehensive dataset of city-pair co-patents from 2005 to 2018, we show that HSR connection significantly increases inter-city co-patents, patent quality, and collaborative partnerships, and such effects are strongest for city-pairs within 250 km and decrease for longer distances. Moreover, the HSR effect is stronger for cities in similar institutional setting, indicating a negative moderating effect of institutional distance. Various robustness methods are used to confirm the validity of our findings.

Keywords: Innovation collaboration, Co-patent, High-speed Rail, Geographical proximity, Institutional proximity

1 Introduction

Inter-city innovation collaborations need to overcome geographic friction. Early research (e.g. Maurseth and Verspagen, 2002; Fischer et al., 2006) that followed Jaffe et al.'s (1993) seminal work found a substantial influence of geographical proximity on innovation collaboration. However, later research that embraced Boschma's (2005) fivefold classification of proximity as an analytical framework has produced the more balanced findings. Firstly, geographical proximity is found to be less influential than previously assumed once non-geographical forms of proximity are considered in innovation collaboration (Torre and Rallet, 2005; Boschma, 2005; Balland et al., 2015). Secondly, geographical and non-geographical forms of proximity are often found to be positively correlated (Balland et al., 2015). Nonetheless, geographical proximity is still found to positively influence the formation of innovation collaboration when other forms of proximity are included in studies (Hong and Su, 2013; Marek et al., 2017; Cao et al., 2019).

If geographical distance remains a noticeable barrier to inter-city innovation collaboration, to what extent do changes in infrastructure counterbalance pre-existing geographic friction and foster innovation collaboration? While the limited studies have shown that reductions in communication costs and travel costs as a result of technological advancement mitigate geographic friction (Agrawal and Goldfarb, 2008; Catalini et al., 2020), these studies also point to the differential impact on innovators across urban systems. For example, Agrawal and Goldfarb (2008) examined the adoption of the Internet on university research collaboration in engineering and found reductions in communication costs increased research collaboration between top-tier and middle-tier institutions from the same region. Catalini et al. (2020) looked at the impact of the introduction of new routes by a low-cost airline on scientist collaboration. They found that reductions in travel costs mitigated geographic friction to collaboration and increased the number of collaborations between 0.3 and 1.1 times. Still, we do not know much about the collaboration-enhancing effect of changes in infrastructure and the cost-induced complementary effect of geographical and institutional proximities.

More recently, the construction of high-speed rail (HSR) in many countries has again raised the question of how HSR can help overcome geographical distance and facilitate inter-city innovation collaboration. Currently, the world has 52,418km of high-speed network in commercial operation and 11,693km of high-speed lines under construction, of which China made up no less than 50% (Guigon, 2020). HSR is one of the most advanced modes of ground transportation that could operate at a speed of over 200 km per hour. As a key national development strategy in China, the construction of a nationwide HSR network aims to improve connectivity between regions and promote a more balanced and equitable regional development (Chen and Haynes, 2017). The sheer scale of HSR connectivity in China, as can be seen in Figure 1, and the advantages of HSR over other alternatives—such as high speed, convenience, comfortable experience, proximity to city centers, punctuality, and safety—have tremendously transformed the way people travel and

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

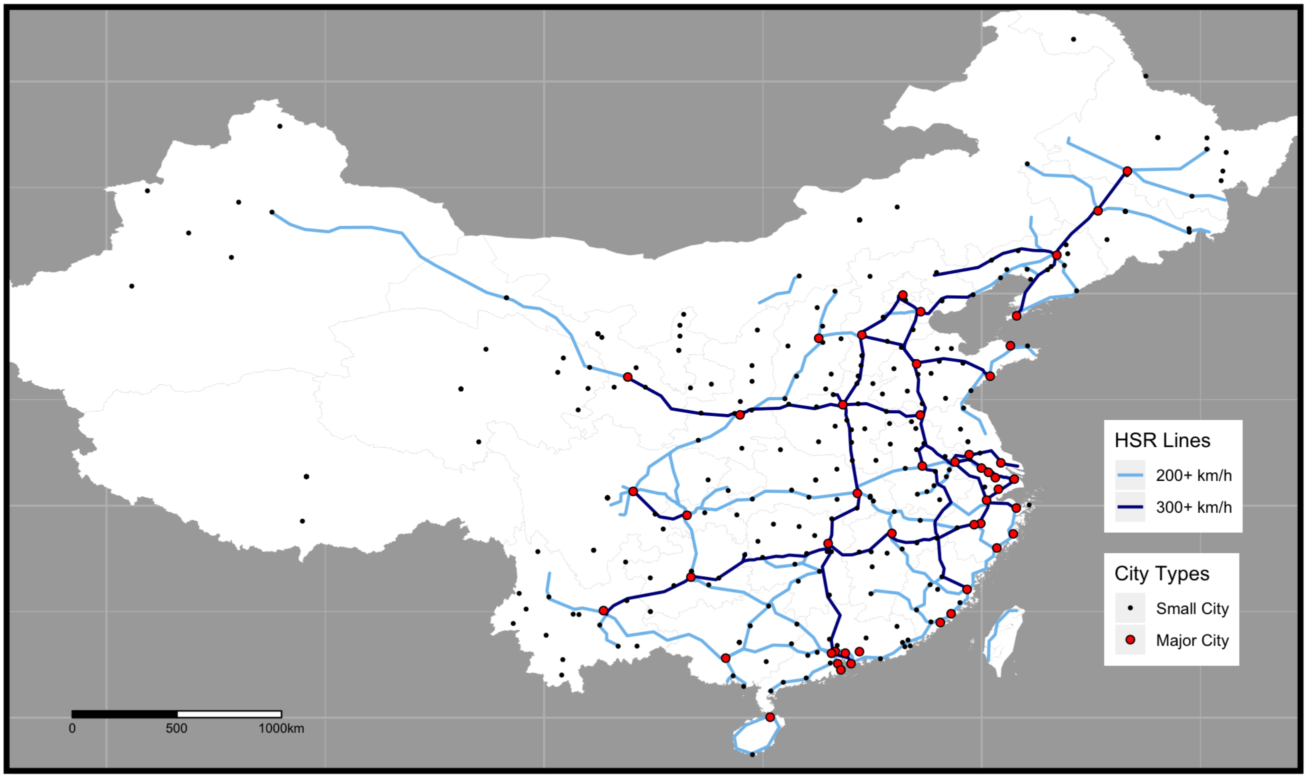


Figure 1: A Map of Chinese HSR Network at the End of 2018

become one of the most popular forms of intercity passenger transportation.

So far, the limited research on HSR and innovation has produced some interesting findings. For example, Inoue et al. (2017) used the case of the opening of the Shinkansen in Japan to estimate the impact of HSR on innovative activities along the line. They found that HSR significantly increased patent submissions and patent citations by establishments along the line. Gao and Zheng (2020) used innovation surveys to assess the impact of HSR on innovation in manufacturing firms in the Yangtze River Delta and Pearl River Delta, China's two most developed regions. The results show that HSR connection promotes firm innovation in peripheral areas. Dong et al. (2019) specifically investigated the impact of HSR on inter-city university research collaboration, using a dataset of research paper publication and citations. They found that when cities are connected by HSR, co-author productivity from existing collaborations rises, new co-author pairs emerge and more highly productive scientists migrate to the HSR cities. Building on studies with a focus on infrastructure and innovation, we aim to unpack the differential impact of HSR by addressing our first research question: To what extent does HSR affect inter-organizational innovation collaboration across HSR-connected cities? First, we use dyadic city-pair co-patent panel data to capture more accurately the differential effect of HSR on intercity co-patent collaboration through two mechanisms, i.e., HSR-induced intensity of face-to-face interactions, and HSR-induced partner matching in larger labor markets. Second, we disentangle the HSR effect across urban systems and on different types of innovators in the manifestation of inter-firm collaboration (II) and university and research institute collaboration (URI).

Extant research on innovation and proximity has explored the impact of institutional proximity on innovation collaboration. As Balland et al. (2015) noted, however, researchers have used two different definitions of institutional proximity, i.e., the degree to which organizations share similar institutional settings at macro level (Boschma, 2005), and values and norms in the same subsystem within academia, industry, or government, following the triple helix model (Etzkowitz and Leydesdorff, 2000; Ponds et al., 2007). As compared to studies that examined the impact of organization-level institutional proximity using the second definition (e.g. Ponds et al., 2007; Hansen, 2015; Cao et al., 2019), the impact of region-level institutional proximity adopting the first definition is under-researched. So far, only two studies can be found. Hong and Su (2013) analyzed the effect of institutional proximity on non-local university-industry collaborations in China. The results show that institutional proximity caused by subordination to the same administrative unit significantly enhances the probability of collaboration, and those effects are more significant when the distance increases, suggesting the substitution effect. Marek et al. (2017) explored the impact of proximity measures on knowledge exchange measured by granted research and development (R&D) collaboration projects in German NUTS-3 regions. They found a 'U'-shaped impact of institutional distance on inter-regional collaboration with a negative impact, which shrinks after passing a distinct threshold level. We complement these works to assess the synergetic effect of HSR and institutional distance from a decentralization perspective. China has an economic system characterized by both high centralization and strong decentralization (Bai et al., 2004). Decentralization comes with local economic agendas and local protection (Bai et al., 2004). This decentralized system has a huge impact on how organizations collaborate. Yet, our understanding of how HSR affects inter-city innovation collaboration in a decentralized institutional system is limited. Our research intends to fill this void by exploring our second research question: to what extent does institutional proximity moderate the HSR-mitigated relationship between geographical proximity and inter-city innovation collaboration?

Our study makes three contributions to the proximity and innovation literature. First, we enrich the literature on geographical proximity and innovation collaboration by unraveling the HSR-mitigated differential effect of geographic friction on the quantity and quality of inter-city innovation collaborations. Second, we draw on a regional decentralization perspective to explore how institutional proximity moderates the HSR effect. Thus, we enrich the literature by providing a more nuanced understanding of how different dimensions of proximity interact to affect inter-city innovation collaboration. Third, we again follow the decentralization perspective to explore whether the HSR effect is more constrained in geographical distance for II collaboration and more constrained in institutional distance for URI collaboration. Our research, therefore, sheds new

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk
For Peer Review Only

light on how different types of innovation actors with varying inherent incentives and behaviors may respond differently to the improved transportation infrastructure and manifest themselves differently in intercity innovation collaboration.

2 Theoretical Framework and Hypothesis Development

For innovation collaboration, face-to-face communication is of importance throughout all stages of the process. At the initial stage, it is essential for firms to match up with the right types of partners—such as vertical (suppliers), horizontal (competitors), or institutional (universities and research institutes) partners—that complement themselves with the necessary knowledge and resources to achieve the goals pursued. Once a partnership or alliance is formed, it is necessary for team members to become familiar with each other, to develop an enhanced understanding of the problem-solving procedure, to cultivate personal trust, and eventually to build effective research routines so as to improve efficiency and prospect for project success (Bercovitz and Feldman, 2011). Therefore, close face-to-face contact is essential throughout the whole process of innovation collaboration.

HSR, as an advanced transportation infrastructure, provides a faster, safer, more comfortable, and arguably the most punctual transportation service than other alternatives, such as regular train, automobile, and air flights (Sun et al., 2017). It fills a blank of traveling at a distance too far for cars and too close for flights. Hence, HSR facilitates more cost-effective inter-city travel for face-to-face contact and collaborative innovation. Overall, HSR affects intercity innovation collaboration through two mechanisms. First, HSR helps increase the intensity of interaction between collaborative partners between connected cities.

HSR connections significantly shrink the geographical distance between cities because of high travel speed at relatively lower costs. This cost-effective transport mode allows team members in inter-organizational collaborative projects to interact face to face more in order to build rapport, share tacit knowledge, and resolve differences. The increasing intensity of interaction has two implications. First, it enhances the efficiency of innovation collaboration that leads to a better performance of co-patenting in quantitative terms. Such an effect should be stronger for city-pairs that within HSR travel time. Studies have shown that within 600km, the HSR travel experience dominates the alternatives, including that of air travel (Lawrence et al., 2019). Therefore, the HSR effect on intercity innovation collaboration should be more salient for city-pairs that are geographically close and within the HSR range. Second, more face-to-face interactions between innovation partners across HSR-connected cities also improve collaborators' cognitive proximity due to greater knowledge sharing, hence elevating innovation outcomes, such as patent quality. Dong et al.'s (2019) research on academic co-publication found the positive effect of HSR on both quantity and quality of co-publication. Therefore, we propose the following.

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk
For Peer Review Only

Hypothesis 1a *HSR increases the quantity of collaborative innovation between connected city-pairs.*

Hypothesis 1b *HSR connection improves quality of collaborative innovation between connected city-pairs.*

Second, HSR increases opportunities for partner matching in larger markets. Firstly, because HSR increases travel speed across cities, it thus creates a larger market for organizations to match partners for innovation projects. The increased cross-city travel speed at lower costs facilitates the better matching of researchers with complementary skills in a larger scientist labor market, leading to the formation of more innovation collaborative partnerships between the connected city-pairs. Secondly, by establishing connections between core markets (megacities) and outside markets (smaller cities), transport improvements expand the geographical reach of knowledge spillover, thereby enabling organizations in outside markets to do new things or to accomplish old tasks in new ways, and energize innovation in other sectors. Accordingly, HSR connections again lead to the formation of more innovation collaborative partnerships between the connected city-pairs. Hence, we propose the following:

Hypothesis 1c *HSR increases the number of innovation collaborative partnerships between connected city-pairs.*

In addition to geographical distance, intercity innovation collaboration can be constrained by the intercity discrepancy in formal and informal institutions (North et al., 1990), or institutional distance. A distinct feature of the economic system in Chins is administrative decentralization (Perkins, 1988). The devolution of decision-making power from the center to local governments allows locally available information to be used more effectively and local preferences to have greater influence over local spending decisions (Chen, 1998). Inevitably, the system leads to the diversity of regulative institutions in terms of rules, laws, and sanctions through the coercive mechanism (Scott, 2013). The unintended consequences of such a decentralized system are local governments' zeal for GDP growth and local protectionism (Bai et al., 2004). Local governments prefer to support local business development and local inter-organizational collaboration as government officers are more likely to get promotions if local economic growth can benefit from significant innovations within their territories (Hong and Su, 2013). Hence, institutional diversity between regions gives rise to unpredictable and unreliable conditions under which effective inter-organizational innovation collaborations are more difficult to take place. Regional institutional discrepancies and protectionism impede cross-region innovation collaboration (Ding and Li, 2015).

Despite lower travel costs incurred by HSR connections, institutional differences persist among provinces. Therefore, the HSR effect is moderated by institutional distance, i.e., HSR connections

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

increase more innovation collaboration between city-pairs that are within the same province than those across provinces. For the aforementioned reasons, we propose the following hypothesis:

Hypothesis 2 *Institutional distance moderates the positive effect of HSR connection on innovation collaboration between connected city-pairs.*

Patents as an embodiment of commericializable technologies are created and applied by various innovative actors. Firms, universities, and research institutions are three key innovative actors in the national innovation system (NIS). It is important to distinguish two types of inter-organizational collaborations, i.e., collaborations involving universities and research institutes (URI)[1] and intra-industrial collaborations (II) because different knowledge types are affected in different dimensions of proximity (Davids and Frenken, 2018). Since most universities and research institutes are public-funded institutions in China, intercity URI collaborations are driven by the government's social and economic policies and aim to produce public goods. In contrast, intercity II collaborations are motivated by business interest and aim to deliver private goods. Comparatively, URI collaborations led by universities and research institutes are influenced by government agendas in the Chinese context, and therefore are less sensitive to economic costs but are more likely to succumb to the stick and carrot approach used by local governments. For such reasoning, we propose the following hypotheses:

Hypothesis 3a *The HSR effect is stronger within close distance for II collaborations than URI collaborations.*

Hypothesis 3b *HSR effect is stronger within the same province for URI collaborations than II collaborations.*

3 Data

3.1 Data and Statistics

Co-patent data from the China National Intellectual Property Administration (CNIPA) is used in this study. We collected data of all patents with two or three applicants over the period of 2005-2018 from the database *incopat.com*.

All co-patent data include two or three applicants who could be individuals, firms, universities, or research institutes. We construct intercity co-patents by using the information of applicant addresses. For a patent with applicants from City A and B, we construct the city-pair as A-B,

[1] URI collaborations include university-university (UU), university-research institutes (UR), university-industry (UI), and research institute-industry (RI). Any co-patents involving universities or research institutes are categorized as URI collaborations.

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

For Peer Review Only

while for three-applicant from City A, B, and C, we then create three city-pairs, A-B, A-C, and B-C but with 1/3 of weight each. There are 293 prefecture cities and 4 municipalities in China in 2018. We only consider the cities that had intercity co-patents and exclude those without, which leaves us a total of 285 prefecture-level and above cities. The original dataset contains 1 million co-patents, and after data cleaning, it is down to 708,002, of which, 386,735 are intercity co-patents. We exclude intracity collaborations in our research sample.

We use three dependent variables. The first is $CoPat_{ijt}$, the count of co-patents between City i and j during the year t as the measure of the quantity of collaborative innovation. The second is the value-weighted patent $CoPatW_{ijt}$ as a measure of the quality of collaborative innovation. The third dependent variable is $CoPatP_{ijt}$ (collaborative partners) as a measure of the quantity of innovation collaborative partnership. Once two organizations cooperate for at least one co-patent in one year, they are defined as innovation collaborative partners.

A city is connected to the HSR network once at least one station is opened. The opening dates and routes of HSR are collected from the official website *12306.cn*, maintained by the National Railway Administration of China. The dummy variable $connect_{ijt}$ is coded one if both the Cities i and j are HSR connected in year t and zero otherwise.

We construct a city-pair panel dataset including all cities with at least one co-patent over 14 years from 2005 to 2018. We exclude the city-pairs that never had any collaborations, and only keep the city-pairs that had at least one collaboration over 14 years. There are a total of 79,058 observations over 14 years on 5,647 unique city-pairs. The main independent variables of interest in addition to $Connect_{ijt}$ are $Distance_{ij}$ and $SameProv_{ij}$, which indicate the distance between Cities i and j and whether the two cities belong to the same province. Geographical distances are measured in straight-line (or Euclidean) distance between cities using geographical information. The literature has used both straight-line distance and travel time to measure geographical distance, but they generate very similar results (Marek et al., 2017). Most of gravity-based models use straight-line distance for its lower cost. Following Hong and Su (2013), we use the provincial-border definition of institutional distance. It implies that cities belonging to the same province are considered institutionally approximate and incur no institutional friction because they are subject to the same regulative institution. For all the specifications, we control city and year fixed effects, which tease out time-invariant city-level characteristics and time trending effects. Besides, we control other time-variant confounding variables that possibly affect the intercity co-patents, including city-level GDP, total single-applicant patents, science and technology government expenditure, etc. Table 1 summarizes the definition and sources of the dependent, independent, and control variables.

Table 2 reports the descriptive statistics of the main dependent and independent variables. As can be seen from the table, the distribution of $CoPat$ is quite skewed with a mean of 4.13 and a standard deviation of 37.02, and a large number of those observations are zeros. In light of con-

For Peer Review Only

Table 1: Variable Definition

Variable	Definition
Outcome Variables:	
$CoPat_{ijt}$:	Total co-patent count between City i and City j
$CoPatW_{ijt}$:	Co-patents weighted by patent values. Patent value is calculated by *incopat.com* using big data technique and including information such as patent citation, assignment, licensing, legal status, and other determinant variables.
$CoPatP_{ijt}$:	Co-patent partnerships between City i and j in year t. Calculated using unique collaborative pairs from the variable $CoPat_{ij}$.
$CoPat(URI)_{ijt}$:	Co-patents involving universities and research institutes between City i and j in year t. $CoPatP(URI)_{ijt}$ is URI partnerships.
$CoPat(II)_{ijt}$:	Intra-firm co-patents between different firms between City i and j in year t. $CoPat(II)_{ijt}$ is II partnerships.
Independent Variables:	
$Connect_{ijt}$:	A time-variant dummy variable indicating whether City i and j are connected to HSR in year t with one year lag. The data is collected from *www.12306.cn*, which maintained by the National Railway Administration of the PRC.
$Distance_{ij}$:	A time-invariant variable measures the straight-line (Euclidean) distance between City i and j in kilometers.
$Dist.S_{(0\sim 250km)}$:	A time-invariant dummy variable coded one when the city-pair is with 250 km distance. $Dist.M_{(250\sim 600km)}$ and $Dist.L_{(600\sim 1000km)}$ are respectively for median and long range dummy variables.
$SamePro_{ij}$:	A time-invariant dummy variable indicating whether City i and j located in the same province.
Control Variables:	
$SinglePat_{it}$:	Total single-applicant patents for City i in year t.
GDP_{it}:	Total gross production in millions.
$SciExp_{it}$:	Government expenditure in science and technology in millions.
$HwayRidership_{it}$:	Total highway ridership in thousands.
$MobileUsers_{it}$:	Total mobile phone users in thousands.
$PatentPerFirm_{it}$:	Total patents per industrial firm.
$S\&TPerFirm_{it}$:	Expenditure in science and technology per industrial firm.
$R\&DPerFirm_{it}$:	R&D employment per industrial firm.
$FIEs_{it}$:	Total foreign invested firms.
$SecondaryShare_{it}$:	Secondary industry output share.
$TertiaryShare_{it}$:	Tertiary industry output share.

For Peer Review Only

siderable over-dispersion and a larger number of zero observations, negative binomial regressions are used throughout the analyses. Table 2 also reports other outcome variables including weighted co-patents, partnerships, and also URI and II co-patents and partnerships.

The correlation analysis in Table 2 suggests the key independent variables such as $Connect$, $SameProv$, and $Distance$ all have relatively low and moderate correlation coefficients with other variables. Moreover, to test multicollinearity, we inspected the variance inflation factors (VIFs) of the variables using linear regression (the convention is to use linear regression when the main

Table 2: Statistics Summary and Correlation Analysis for the Main Dependent and Independent Variables

	Variables	Observations	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	$CoPat$	79058.00	4.13	37.02	1.00													
2	$CoPatW$	79058.00	4.18	37.95	0.99	1.00												
3	$CoPat(Top)$	79058.00	2.31	21.60	0.96	0.98	1.00											
4	$CoPatP$	79058.00	1.34	7.40	0.80	0.79	0.75	1.00										
5	$CoPat(II)$	79058.00	3.07	31.99	0.98	0.97	0.94	0.73	1.00									
6	$CoPat(URI)$	79058.00	1.06	8.72	0.66	0.65	0.62	0.75	0.49	1.00								
7	$CoPatP(II)$	79058.00	0.69	4.18	0.81	0.80	0.75	0.96	0.76	0.64	1.00							
8	$CoPatP(URI)$	79058.00	0.65	3.56	0.72	0.71	0.67	0.95	0.61	0.80	0.83	1.00						
9	$Connect.lag1$	79058.00	0.25	0.43	0.12	0.11	0.11	0.17	0.10	0.12	0.16	0.17	1.00					
10	$Distance$	79058.00	939.12	635.20	-0.03	-0.03	-0.03	-0.05	-0.03	-0.04	-0.04	-0.05	-0.01	1.00				
11	$SameProv$	79058.00	0.14	0.35	0.01	0.01	0.01	0.03	0.00	0.05	0.01	0.06	-0.04	-0.46	1.00			
12	$Dist.S_{(0\sim250km)}$	79058.00	0.10	0.30	0.04	0.04	0.03	0.08	0.02	0.07	0.05	0.10	-0.01	-0.44	0.66	1.00		
13	$Dist.M_{(250\sim600km)}$	79058.00	0.25	0.43	-0.00	-0.00	-0.01	-0.01	0.00	-0.01	-0.01	-0.01	-0.00	-0.49	0.11	-0.20	1.00	
14	$Dist.L_{(600\sim1000km)}$	79058.00	0.24	0.43	-0.01	-0.01	-0.01	-0.02	-0.01	-0.02	-0.01	-0.02	0.03	-0.13	-0.22	-0.19	-0.32	1.00

For Peer Review Only

regression model is non-linear). The VIFs value for $Connect$, $SamePro$, and $Distance$ are respectively 5.1, 1.66, and 1.68 , which are below the acceptable level of 10 (Neter et al., 1996). Hence, multicollinearity is not a concern in our case.

4 Empirical Strategy and Results

We apply a difference-in-differences (DID) approach to test the effects of HSR on intercity innovation collaboration. Because intercity innovation collaborations are dyadic in nature, we apply a variant of gravity model—an empirical method originally used in international trade literature, and then increasingly adopted in invention collaboration and knowledge flow literature (Picci, 2010; Cappelli and Montobbio, 2016). Our regional gravity model considers innovation collaboration in three measures as a function of the distance between cities and time-variant economic variables that potentially affect inter-city innovation collaboration. We formulate the following baseline regression model:

$$Y_{ijt} = \alpha_0 + \alpha_1 Connect_{ijt} + \alpha_2 Dist_{ij} + \alpha_3 SameProv_{ij} + X\beta + \delta_i + \delta_j + \tau_t + \epsilon_{ijt} \qquad (1)$$

The main variable of interest is $Connect_{ijt}$, the one-year lagged dummy variable indicating whether City i and City j are both connected to the HSR network in the year t-1[2]. $Dist_{ij}$ is a continuous variable of the straight-line distance between City i and City j in kilometers. $SameProv_{ij}$, a dummy variable, indicates whether two cities are located in the same province, which is interpreted as institutional proximity. X stands for the time-variant control variables for City i and j. δ_i and δ_j indicate the fixed-effects of City i and City j respectively. τ_t is the year dummy and ϵ_{ijt} is the error term.

The data and method we use have two advantages. First, we use a full set of Chinese co-patent data across all industries, so our data are representative of all ranges of technologies. Second, dyadic city-pair observations combined with the gravity model could better identify the effects of geographical and institutional distance. In all estimations, we apply the negative binomial gravity model framework.

[2]We use a binary dummy variable indicating whether a city is connected to the HSR network for two reasons. First, easier interpretation—using binary variables we can interpret the results as treatment effect. A continuous variable such as volume or number of trains can be difficult to interpret. Second, the HSR effect is unlikely to be linear in relation to the volume or numbers of trains.

For Peer Review Only

4.1 The Baseline Result

Table 3 presents the baseline results from three model specifications. Model (1) excludes city-level variables and fixed effects. From pooled regression in Model (1), HSR connections show a positive and significant effect, meaning connected city-pairs tend to have a larger number of co-patents than those unconnected.

Table 3: The Baseline Regression of Negative Binomial Regressions

	Dependent Variable: $CoPatent$		
	(1)	(2)	(3)
$Connect$	1.972***	0.009	0.042
	(0.059)	(0.056)	(0.071)
$Distance$	−0.001***	−0.001***	−0.001***
	(0.0001)	(0.0001)	(0.00004)
$SameProv$	−0.121	1.312***	1.431***
	(0.087)	(0.057)	(0.050)
$Dist.S_{(0\sim250km)}$		0.344***	
		(0.097)	
$Dist.M_{(250\sim600km)}$		−0.004	
		(0.078)	
$Dist.L_{(600\sim1000km)}$		−0.021	
		(0.060)	
$Connect \times Dist.S_{(0\sim250km)}$		0.261***	
		(0.075)	
$Connect \times Dist.M_{(250\sim600km)}$		0.131*	
		(0.073)	
$Connect \times Dist.L_{(600\sim1000km)}$		−0.051	
		(0.069)	
$Connect \times Distance$			−0.00002
			(0.00005)
$Connect \times SameProv$			0.301***
			(0.077)
$CityPair\ Controls$	No	Yes	Yes
$City\&Year\ FE$	No	Yes	Yes
Observations	79,058	78,834	78,834
Akaike Inf. Crit.	201,818.700	170,575.300	170,666.300

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors are clustered at the city level.

In Model (2), we additionally control for the interaction term of distance ranges with HSR connection: $Connect \times (Dist.S + Dist.M + Dist.L)$. $Dist.S$ is coded as one if the city-pair is within 250km distance range, about 1.5 hours travel time by HSR. Similarly, $Dist.M$ and $Dist.L$ indicate city-pairs of distance ranging from 250 to 600 km and from 600 to 1000 km. The interaction coefficients of *connect* with the range dummy variables suggest the extent to which HSR connection

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk
For Peer Review Only

increases the number of co-patents between city-pairs within those ranges. The coefficient of $Connect \times Dist.S_{(0\sim250km)}$ is significant and positive at 0.261, meaning that HSR is effective in increasing innovation collaborations between connected city-pairs within 250km by 26.1%. From 250 to 600 km, though insignificant, HSR connection accounts for a 13.1% increase in co-patents, while from 600 to 1000 km, the effect is negative. Therefore, the results of Model (2) support Hypothesis 1a, indicating that HSR connection increases intercity innovation collaborations. The HSR effect is most significant within 250 km but diminishes by longer distances.

Model (3) additionally controls for the interaction term: $Connect \times (Distance + SameProv)$, which is to examine whether being in the same province, conditional on geographical distance, moderates the effect of HSR connection. The interaction shows a positive and significant effect at 0.301, suggesting that HSR connection increases by 30.1% for cities that are within the same province after controlling for geographical distance. That is, institutional proximity complements HSR connection in facilitating intercity co-patents. In other words, the HSR effect is moderated by institutional distance. Hence, it supports Hypothesis 2.

4.2 Innovation Quality and Partnerships

To test the effect of HSR connection on quality of co-patent value and the number of collaborative partnerships, we use the same regression specifications as in Model (2) and (3) from Table 3, but with different dependent variables.

In Table 4, Columns (1) and (3) report the interaction effect within different distance ranges, and Columns (2) and (4) report the interaction with institutional proximity. For regressions on value-weighted co-patents, Column (1) suggests that HSR connect increases value-weighted co-patents by 28.5% within 250km, higher than 26.1% in the simple patent count in the baseline estimation. The difference suggests that the increased innovation collaborations as a result of HSR connection also tend to produce higher innovation value, hence confirming Hypothesis 1b. Column (2) shows that HSR connection increases valued-weight co-patents by 30.4%, which is similar to 30.1% in the baseline estimate, suggesting that co-patent quality increases for collaboration between cities of geographical proximity but not institutional proximity.

Regressions on co-patent partnerships in Columns (3) and (4) reveal slightly differential HSR effects on the dimension of geographical and institutional proximity. On one hand, there is a weak significant HSR effect on forming collaborative partners for cities of geographical proximity, indicating that most of the increased co-patents are from the deepening of existing collaborative partnerships. On the other, HSR connection increases collaborative partners for cities of institutional proximity (being in the same province). Hence, there are both deepening and widening effects on collaboration between cities of the same province. A further analysis, which breaks down the types of innovators, reveals a more nuanced pattern of how HSR affects intercity collaborative partnerships where Hypothesis 1c can be partially supported.

Table 4: Regressions on Value Weighted Co-patents and Partnerships

	Dependent Variable:			
	Value-weighted		Partnerships	
	(1)	(2)	(3)	(4)
$Connect$	0.009	0.063	−0.007	−0.102**
	(0.083)	(0.097)	(0.048)	(0.043)
$Distance$	−0.001***	−0.001***	−0.001***	−0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$SameProv$	1.415***	1.543***	1.264***	1.487***
	(0.134)	(0.122)	(0.104)	(0.087)
$Connect \times Dist.S_{(0\sim250km)}$	0.285***		0.102*	
	(0.105)		(0.061)	
$Connect \times Dist.M_{(250\sim600km)}$	0.164		−0.049	
	(0.125)		(0.056)	
$Connect \times Dist.L_{(600\sim1000km)}$	−0.058		−0.031	
	(0.146)		(0.064)	
$Connect \times Distance$		−0.00003		0.0001
		(0.0001)		(0.00005)
$Connect \times SameProv$		0.304***		0.223***
		(0.114)		(0.064)
$Control\ Variables$	Yes	Yes	Yes	Yes
$City, Year\ FE$	Yes	Yes	Yes	Yes
Observations	78,834	78,834	78,834	78,834
Akaike Inf. Crit.	156,252.300	156,339.900	138,473.600	138,896.600

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the city level. The odd-number columns follow the Model (3), and the even-number columns follows Model (4) in the baseline results of Table 3. Some non-essential variables are omitted.

4.3 Comparison between URI and II Collaborations

Table 5 presents the regression results that explore the difference between URI and II co-patents. Columns (1) and (5) are regressions on co-patent counts, which shows that HSR connection increases II co-patents by 27.6% and URI co-patents by 18.9%, suggesting the greater effect of HSR connection on II than URI collaboration within 250 km. Between 250 and 600km, the coefficient is also greater for II than URI collaborations, but both effects are insignificant. Columns (3) and (7) are regressions on collaborative partnerships, which show that HSR connection has a positive and significant effect on the formation of innovation partnerships for II but not for URI collaborations. Together, the results confirm our hypothesis 3a, indicating that HSR connection has a greater effect on II than URI collaborations so far as geographical dimension is concerned.

For Columns (2), (4), (6), and (8), the regressions explore the effect of institutional dimension on HSR connection and both II and URI collaborations. The coefficients on $Connect \times SameProv$ suggest that HSR connection increases within provincial innovation collaborations more for URI and II types. For II co-patents, the HSR effect on co-patent count is weakly significant at 0.198

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

Table 5: Regression Comparison between URI and II Co-patents

	Dependent Variable: Co-patent Count and Partnerships							
	II-CoPatents		II-Partnerships		URI-CoPatents		URI-Partnerships	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Connect	−0.043	0.039	−0.029	−0.067	0.042	−0.157*	0.010	−0.257***
	(0.094)	(0.102)	(0.074)	(0.073)	(0.047)	(0.083)	(0.047)	(0.063)
Distance	−0.001***	−0.001***	−0.001***	−0.001***	−0.0005***	−0.001***	−0.0005***	−0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
SameProv	1.201***	1.272***	0.993***	1.156***	1.640***	1.870***	1.629***	1.863***
	(0.138)	(0.101)	(0.115)	(0.085)	(0.096)	(0.110)	(0.096)	(0.100)
$Connect \times Dist.S_{(0\sim 250km)}$	0.276**		0.165*		0.189**		−0.013	
	(0.122)		(0.094)		(0.086)		(0.086)	
$Connect \times Dist.M_{(250\sim 600km)}$	0.149		−0.002		−0.053		−0.134**	
	(0.135)		(0.076)		(0.067)		(0.067)	
$Connect \times Dist.L_{(600\sim 1000km)}$	−0.013		0.033		−0.165***		−0.136**	
	(0.150)		(0.090)		(0.053)		(0.053)	
$Connect \times Distance$		−0.00004		0.00004		0.0001*		0.0002***
		(0.0001)		(0.0001)		(0.0001)		(0.0001)
$Connect \times SameProv$		0.198		0.209***		0.435***		0.311***
		(0.147)		(0.074)		(0.134)		(0.083)
City Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	79,058	79,058	79,058	79,058	79,058	79,058	79,058	79,058
Akaike Inf. Crit.	119,984.300	120,002.100	94,778.950	94,926.000	105,502.600	105,744.000	93,477.190	93,894.030

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the city level. Some non-essential variables are omitted.

For Peer Review Only

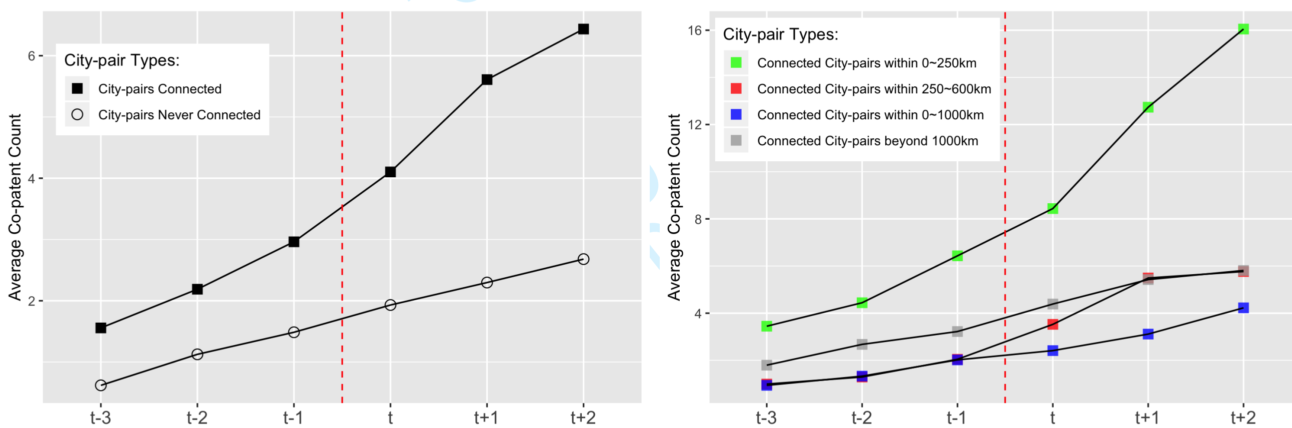
and the effect on the formation of partnerships is 0.209. Both numbers are noticeably smaller than the coefficient for URI at 0.435 and 0.311. Thus comparison of HSR effect on II and URI collaborations again confirms Hypothesis 3b.

5 Robustness Check

5.1 Test of Parallel Trend Assumption

The validity of DID method hinges on two key assumptions, namely the parallel trend assumption and exogeneity of HSR connections. We graphically illustrate the trends of co-patents between different types of city-pairs. Figure 2 illustrates the trend comparison of different city-pairs.

Figure 2: Trends Comparisons before and after the HSR Openings

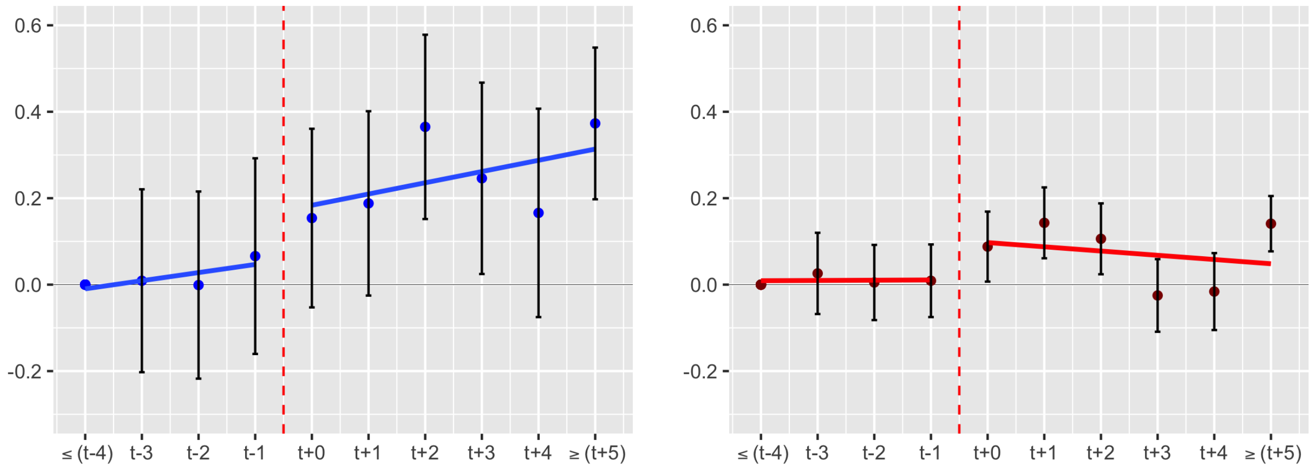


Note: Since HSR connection took place in different years over time, we align the opening year at time t. The red dashed line indicates the event of HSR connection dividing the pre- and post-periods. The left panel compares the connected and the unconnected city-pairs. The right panel compares the connected city-pairs of different distance in-between.

The left panel compares the trend of connected and non-connected city-pairs, and the right illustrates the trends of connected city-pairs of different distance ranges. At a glance, the pre-treatment lines followed a relatively close trend with each other. However, when inspecting more closely, there is a slight divergence visible at year t-1, which also shows up in Figure 3 that there is a slight jump in year t-1. Given that all variables are random, a slight divergence is acceptable. Nonetheless, we argue that the slight divergence in parallel trends is likely the result of the 'step ahead' effect. That is, organizations may move ahead to carry out more collaborative activities in anticipation of HSR connection. As R&D and innovations are long-term projects, in the foresight of better connectivity and more convenient travel, firms may move ahead to increase collaboration with partners that are more accessible in the near future. We argue that the "step-ahead" effect differs from a secular divergent effect and does not carry into the following periods.

For Peer Review Only

Figure 3: The Dynamics of HSR Effects: Co-patents and Partnerships



Note: We run the same fixed-effects regression model with indicator variables corresponding to three years before and 6 years after HSR connection. The left panels reports the regression coefficients of co-patents and the right panel reports the coefficients of the partnerships. The vertical bars represent 90% confidence internal.

For Peer Review Only

To test whether the slight divergence is within statistical tolerance, we construct an event study to investigate the dynamics of HSR effects in specific years before and after connection. Figure 3 illustrates those coefficient estimates for individual years. On the left panel, the blues dots indicate the estimated coefficients of HSR connection on co-patents for city-pairs within 250km. The three years before connection had a weak effect, while the effect of post-connection started to pick up and peaked in year t + 2, two years after connection. The right panel shows the effect on collaborative partnerships. Similar to the effect on co-patents, the pre-connection years showed little effect, while intercity collaborative partnerships started to establish from $t+0$ to $t+3$. The results of the event study again confirm that the parallel trend assumption holds and that the increased intercity co-patents and partnerships occur likely as a result of the construction of the HSR network.

Furthermore, we conduct a placebo test to check whether the identified HSR effect could be contaminated by the pre-treatment trend. The results (available in the online Appendix) confirm that the parallel trend assumption required in the DID method is satisfied.

5.2 Test of Endogeneity

Another potential identification issue is endogeneity resulting from reverse causality. If planning of HSR routes were to be based on the expectation that some cities tend to engage more in collaborative activities, then HSR connection would be endogenous due to reverse causality. Following Dong et al. (2019), we use historical rail connection and city-level elevation as instrumental variables (IVs) and adopt a two-stage least square (2SLS) approach to test endogeneity. The results (available in the online appendix) confirm that findings from our DID analysis are robust. Taken together, the results of trends comparison, event study, and IV regression all confirm that our DID analysis satisfies its key assumptions and that our findings are robust.

5.3 Marketization Index as a Measure of Institutions

In this study, we follow Hong and Su (2013) and use a province-border measure of institutional distance. We find evidence to confirm that institutional distance moderates the positive effect of HSR connection on innovation collaboration between connected city-pairs. To test the robustness of our results, we use the marketization index as an alternative measure of institutional distance. Marketization index (MI) is a frequently used measure of institutional quality in China (Li et al., 2006; Firth et al., 2009). It measures the extent to which Chinese provinces progress toward a fully-fledged market economy under economic reform (Bin et al., 2020). Using MI as an alternative measure of institutional distance, we find consistent evidence (available in the online appendix) with one that uses province-border as a measure of institutional distance. The additional analysis thus confirms that our main thesis regarding the effect of institutional distance remains robust.

5.4 Heterogenous Effect on Cities of Different Sizes

To test the heterogeneity of treatment effect among cities of different sizes, we further conduct a subsample analysis on cities of different sizes. We split Chinese cities into 49 major and 236 small cities. To disentangle the effect of HSR, we separate the observations into three types: major-major, major-small, and small-small. We run sub-sample regressions of the three types of city-pairs (detailed in online Appendix). Table A4 (online Appendix) reports the HSR effects on city-pairs of different size combinations. The analysis reveals three additional intriguing results. First, the most significant HSR effect comes from between major-small city-pairs. HSR connection increases the number of co-patents by 22.6% within 250 km, 13.9% within 600 km, and 33% within the same province for the major-small city-pairs. Second, for large-large city-pairs, the significant HSR effect (20.8 % increase) is only found within 250 km, and the effect is more pronounced (29.4% increase) within the same province. Third, HSR connection has insignificant effect on innovation collaborations in small-small city-pairs.

6 Discussion and Conclusion

In this paper, we investigate the effect of HSR on intercity innovation collaboration. Using the massive construction of the HSR network in China as a quasi-natural experiment with a variety of econometric approaches, we find that HSR connections increase collaboration quantity (co-patents) and quality (value-weighted co-patents) by 26.1% and 28.6% respectively for city-pairs within 250

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

km. The HSR effect diminishes after 250km and disappears beyond 600km. Institutional proximity positively moderates the HSR effect, i.e., the HSR effect for city-pairs of the same provinces is stronger than for those across different provinces. Further analyses show that the HSR effect on II co-patents is greater than URI co-patents within 250 km, while the HSR effect is stronger for URI than II co-patents within the same province. Our research contributes to the literature on collaboration in several ways.

First, our research provides a more nuanced understanding of the HSR effect on intercity innovation collaboration. Our research investigates inter-organizational collaborations and finds a similar HSR effect on the quantity and quality of co-patenting between connected city-pairs, thus enriching the evidence base of the HSR and innovation collaboration literature. Moreover, extant research is inconsistent on whether HSR has the "polarized-effect" or "leveling-up effect". For example, some studies found that HSR enhances the economy of core cities or large cities at the expense of smaller cities (e.g. Monzón et al., 2013; Ke et al., 2017; Vickerman, 2018). On the contrary, some studies found that HSR creates new locational advantages for small cities (e.g. Sasaki et al., 1997; Chen and Haynes, 2017). Dong et al.'s (2019) research on academic co-publication found that HSR increases co-authors' productivity and cooperation among authors from central and secondary cities. The evidence from our research on inter-organizational collaboration does not dismiss the "polarized effect" of HSR as we find the significant HSR effect on innovation collaboration is only found for large-large city-pairs within 250 km. However, our findings lean more towards the "leveling-up" effect as we find that the HSR effect is more pronounced on co-patenting between major-small city-pairs up to the geographical distance of 600 km. While our research observes the tendency of innovation collaboration between large cities, we nonetheless find that HSR networks help reconfigure the national innovation system by expanding the system's reach to smaller cities.

Second, our research contributes to the understanding of the complementary effect between geographical distance and institutional distance on innovation collaboration. In the limited literature that adopts the definition of institutional proximity at the macro level, Hong and Su's (2013) research implies a substitution effect between geographical proximity and institutional proximity. Marek et al.'s (2017) research a U-shaped effect of institutional distance on inter-regional innovation collaboration. We extend this line of research to account for changes in the infrastructure on collaboration in the case of HSR. We particularly embed our arguments in the decentralization perspective. We find that institutional friction remains persistent even after cities are connected by HSR. As a result, the positive effect of lower travel costs is weakened by persistent institutional friction, suggesting that HSR benefits are moderated among cities across different provinces. Our research thus implies that the impact of HSR on intercity innovation collaboration would be greater if local protectionism in the decentralization system were to be weakened.

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk
For Peer Review Only

Third, we enrich the literature of transportation infrastructure and intercity collaboration with empirical evidence that shows that HSR connections affect URI and II collaborations differently.

The findings of this study have practical implications for policymakers. Recent studies suggest intercity collaboration linkages improve cities' innovation capacity (Cao et al., 2021). Hence, to best capitalize on the effect of HSR, policymakers need to pursue a synergetic development plan of transportation and intercity innovation collaboration network. Local governments could work together and toward eliminating the persistent presence of institutional friction that weakens the benefits of HSR connection, especially on URI innovation collaboration, freeing up the flow of knowledge and innovative resource to form a more integrated national innovation system. As HSR connection presents an opportunity for innovators in small cities to form collaborative projects with the major cities where innovative resources are more abundant, the local policymakers should create accommodation and encourage such collaboration with the major cities.

This study has limitations. First, our research only captures the partial effect of HSR connection on innovation collaboration because collaborative innovation activities do not always produce patentable technologies. A comprehensive measurement of collaborative innovation activities, if possible, would improve analyses and estimates. Second, our research does not directly measure the travel cost of HSR relative to other modes of transport. Yet, the question of how HSR saves travel costs to enhance innovation collaboration can be interesting and worth exploring. Third, future work could extend to investigations into how HSR connections affect other forms of intercity open innovation practices, such as intercity technology licensing and joint ventures.

References

Agrawal, Ajay and Avi Goldfarb, "Restructuring Research: Communication Costs and the Democratization of University Innovation," *American Economic Review*, August 2008, *98* (4), 1578–1590.

Bai, Chong-En, Yingjuan Du, Zhigang Tao, and Sarah Y Tong, "Local protectionism and regional specialization: evidence from China's industries," *Journal of international economics*, 2004, *63* (2), 397–417.

Balland, Pierre-Alexandre, Ron Boschma, and Koen Frenken, "Proximity and Innovation: From Statics to Dynamics," *Regional Studies*, June 2015, *49* (6), 907–920.

Bercovitz, Janet and Maryann Feldman, "The mechanisms of collaboration in inventive teams: Composition, social networks, and geography," *Research Policy*, 2011, *40* (1), 81–93.

Bin, Peng, Xiaolan Chen, Andrea Fracasso, and Chiara Tomasi, "Firm employment growth in China: The role of marketization and regional economic factors," *Growth and Change*, March 2020, *51* (1), 402–439.

Boschma, Ron, "Proximity and innovation: a critical assessment," *Regional studies*, 2005, *39* (1), 61–74.

Cao, Zhan, Ben Derudder, and Zhenwei Peng, "Interaction between different forms of proximity in inter-organizational scientific collaboration: The case of medical sciences research

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk
For Peer Review Only

network in the Yangtze River Delta region," *Papers in Regional Science*, 2019, *98* (5), 1903–1924.

_ , _ , Liang Dai, and Zhenwei Peng, "'Buzz-and-pipeline' dynamics in Chinese science: the impact of interurban collaboration linkages on cities' innovation capacity," *Regional Studies*, April 2021, pp. 1–17.

Cappelli, Riccardo and Fabio Montobbio, "European integration and knowledge flows across European regions," *Regional Studies*, 2016, *50* (4), 709–727.

Catalini, Christian, Christian Fons-Rosen, and Patrick Gaulé, "How Do Travel Costs Shape Collaboration?," *Management Science*, 2020. Publisher: INFORMS.

Chen, Kang, "Administrative decentralisation and changing state-society relations in china," *International Journal of Public Administration*, 1998, *21* (9), 1223–1255.

Chen, Zhenhua and Kingsley E Haynes, "Impact of high-speed rail on regional economic disparity in China," *Journal of Transport Geography*, 2017, *65*, 80–91.

Davids, Mila and Koen Frenken, "Proximity, knowledge base and the innovation process: towards an integrated framework," *Regional Studies*, 2018, *52* (1), 1–12.

Ding, Xuedong and Jun Li, *Incentives for innovation in China: Building an innovative economy*, Routledge, 2015.

Dong, Xiaofang, Siqi Zheng, and Matthew E Kahn, "The Role of Transportation Speed in Facilitating High Skilled Teamwork Across Cities," *Journal of Urban Economics*, 2019, p. 103212.

Etzkowitz, Henry and Loet Leydesdorff, "The dynamics of innovation: from National Systems and "Mode 2" to a Triple Helix of university–industry–government relations," *Research Policy*, February 2000, *29* (2), 109–123.

Firth, Michael, Chen Lin, Ping Liu, and Sonia M L Wong, "Inside the black box: Bank credit allocation in China's private sector," *Journal of Banking & Finance*, 2009, p. 12.

Fischer, Manfred M, Thomas Scherngell, and Eva Jansenberger, "The geography of knowledge spillovers between high-technology firms in Europe: Evidence from a spatial interaction modeling perspective," *Geographical Analysis*, 2006, *38* (3), 288–309.

Gao, Yanyan and Jianghuai Zheng, "The impact of high-speed rail on innovation: An empirical test of the companion innovation hypothesis of transportation improvement with China's manufacturing firms," *World Development*, 2020, *127*, 104838.

Guigon, Marc., "The perpetual growth of high-speed rail development," *Global Railway Review*, 2020.

Hansen, Teis, "Substitution or overlap? The relations between geographical and non-spatial proximity dimensions in collaborative innovation projects," *Regional Studies*, 2015, *49* (10), 1672–1684.

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

Inoue, Hiroyasu, Kentaro Nakajima, and Yukiko Umeno Saito, *The Impact of the opening of high-speed rail on innovation*, RIETI, 2017.

Jaffe, Adam B, Manuel Trajtenberg, and Rebecca Henderson, "Geographic localization of knowledge spillovers as evidenced by patent citations," *the Quarterly journal of Economics*, 1993, *108* (3), 577–598.

Ke, Xiao, Haiqiang Chen, Yongmiao Hong, and Cheng Hsiao, "Do China's high-speed-rail projects promote local economy?—New evidence from a panel data approach," *China Economic*

For Peer Review Only

Review, 2017, *44*, 203–226.

Lawrence, Martha, Richard Bullock, and Ziming Liu, *China's high-speed rail development* 2019. OCLC: 1101272415.

Li, Hongbin, Lingsheng Meng, and Junsen Zhang, "Why Do Entrepreneurs Enter Politics? Evidence from China," *Economic Inquiry*, July 2006, *44* (3), 559–578.

Marek, Philipp, Mirko Titze, Clemens Fuhrmeister, and Ulrich Blum, "R&D collaborations and the role of proximity," *Regional Studies*, December 2017, *51* (12), 1761–1773.

Maurseth, Per Botolf and Bart Verspagen, "Knowledge spillovers in Europe: a patent citations analysis," *Scandinavian Journal of Economics*, 2002, *104* (4), 531–545.

Monzón, Andrés, Emilio Ortega, and Elena López, "Efficiency and spatial equity impacts of high-speed rail extensions in urban areas," *Cities*, 2013, *30*, 18–30.

Neter, John, Michael H Kutner, Christopher J Nachtsheim, William Wasserman et al., *Applied linear statistical models*, Irwin Chicago, 1996.

North, Douglass C et al., *Institutions, institutional change and economic performance*, Cambridge university press, 1990.

Perkins, Dwight Heald, "Reforming China's economic system," *Journal of Economic Literature*, 1988, *26* (2), 601–645.

Picci, Lucio, "The internationalization of inventive activity: A gravity model using patent data," *Research Policy*, 2010, *39* (8), 1070–1081.

Ponds, Roderik, Frank Van Oort, and Koen Frenken, "The geographical and institutional proximity of research collaboration," *Papers in regional science*, 2007, *86* (3), 423–443. Publisher: Wiley Online Library.

Sasaki, Komei, Tadahiro Ohashi, and Asao Ando, "High-speed rail transit impact on regional systems: does the Shinkansen contribute to dispersion?," *The annals of regional science*, 1997, *31* (1), 77–98.

Scott, W Richard, *Institutions and organizations: Ideas, interests, and identities*, Sage publications, 2013.

Sun, Xiaoqian, Yu Zhang, and Sebastian Wandelt, "Air transport versus high-speed rail: an overview and research agenda," *Journal of Advanced Transportation*, 2017, *2017.*

Torre, Andre and Alain Rallet, "Proximity and Localization," *Regional Studies*, February 2005, *39* (1), 47–59.

Vickerman, Roger, "Can high-speed rail have a transformative effect on the economy?," *Transport Policy*, 2018, *62*, 31–37.

For Peer Review Only

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

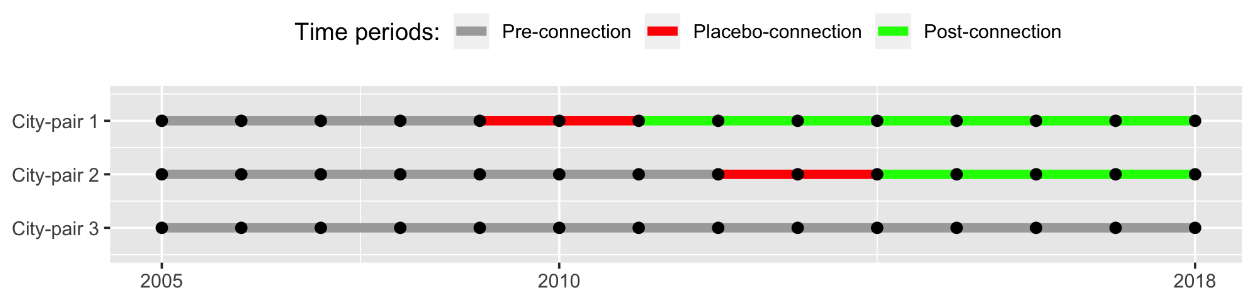
Online Appendix

In this appendix, we report several robustness checks we have carried out. Section 1.1 reports the placebo test to check whether a counter-factual treatment would generate positive and significant effects. Together with the event study, it is to ensure our analysis satisfies the common trend assumption. Section 1.2 reports the robustness check to see our main results hold when we use the marketization index as an alternative measure of institutional distance. Section 1.3 conducts sub-sample analysis and explores the heterogenous HSR effect among cities of different sizes. Section 1.4 reports the instrument variable regression to test the potential endogeneity problem.

1.1 Placebo Test

In conducting a placebo test, we aim to check whether the identified effect could be contaminated by the pre-treatment trend. We create a placebo treatment of HSR connections using two years prior to the actual opening year and remove all observations with actual HSR connections. Figure A1 shows how the placebo variable is created.

Figure A1: Visual Illustration of Placebo Variable Construction



Note: This is a graphical illustration of how the placebo variable is constructed. The X-axis is the time horizon from 2005 to 2018, while the Y-axis is three typical city-pairs. City-pair 1 and 2 are HSR-connected during a year, while city-pair 3 is never connected. To constructed the placebo variable, first, all post-connection period observations, as indicated by the green color, are deleted. Second, a placebo, as indicated by the red color, is created for the connected city-pairs for two periods before the true connection year. If the regression result shows the significance of the placebo effect, then the equal trend assumption is rejected.

Table A1 reports the regression results using placebo variable designed. Column (1) shows that the coefficient of *Placebo* is insignificant at 0.105, suggesting that right before the HSR connection there is no significant trend between the connected and the unconnected. The interaction term of *Placebo* with *Dist.S* suggests between 0 to 250km, the placebo effect is insignificant and with a low positive effect. The interaction term of *Dist.M* suggests that city-pairs between 250 to 600km apart experienced a 27.4% reduction during two years prior to the HSR connection. The interaction term of *Dist.L* is insignificant.

For Peer Review Only

Table A1: The Placebo Test

	Dependent Variable: Co-patent Counts	
	(1)	(2)
$Plcebo$	0.105 (0.069)	0.061 (0.087)
$Plcebo \times Dist.S_{(0\sim250km)}$	0.043 (0.103)	
$Plcebo \times Dist.M_{(250\sim600km)}$	-0.206^{**} (0.091)	
$Plcebo \times Dist.L_{(600\sim1000km)}$	-0.035 (0.096)	
$Plcebo \times Distance$		0.00004 (0.0001)
$Plcebo \times SameProv$		0.012 (0.105)
$Control\ Variables$	Yes	Yes
$City, Year\ FE$	Yes	Yes
Observations	55,013	55,013
Akaike Inf. Crit.	81,965.050	82,073.530

Note: There are 23,924 city-pair-year observations were omitted from total 79,058 observations. All 55,013 are non-connected city-pair-year observations.

Overall, the parallel trend required in the DID method is satisfied. For the middle ranged city-pairs, there is a noticeable fall before HSR connection. We argue that it does not change the results because even if the trend for the middle ranged city-pair is to decrease the co-patents, the DID estimate can be interpreted as the lowered bound. Moreover, the parallel assumption on the city-pairs within 250 km holds well and hence the main results are robust.

Column (2) confirms the parallel assumption between the connected and the unconnected and also between city-pairs within and across provinces.

1.2 Marketization Index as a Measure of Institution Proximity

In this study, we follow Hong and Su (2013) and use a province-border measure of institutional friction. It implies that cities belonging to the same province are considered institutionally approximate and incur no institutional friction because they are subject to the same political, legal, and regulatory influences. To test the robustness of our results, we use the marketization index as an alternative measure of institutional friction. Marketization index (MI) is also a frequently used measure of institutional quality in China (Chen et al., 2006; Li et al., 2006; Firth et al., 2009) since it indicates how Chinese provinces progress toward the realization of a fully-fledged market economy under economic reform (Bin et al., 2020). The index is composed of five pillars that reflect the different aspects of the marketization process, namely development of intermediate organization and law, government-market relation, private economic development, product market development, and factor market development (Wang et al., 2017). A province's score in the marketization index is the aggregate score of all sub-indices in five pillars. MI was developed by the National Economic Research Institute (NERI), an influential think tank in China, and the

For Peer Review Only

first MI report was published in 2000. Following Mao and Mao (2021), we calculate the intercity institutional friction (or institutional distance) using the following equation:

$$Institutional.dist = \sum_{k}^{5}[(I_{k,i} - I_{k,j})^2/V_k]/5 \tag{1}$$

where I_k, i is the marketization index k for city i, V_k is the variance of institutional score of kth pillar. As the marketization index is measured at the provincial level, we additionally define Institutional distance between cities of the same province is zero because cities in the same province tend to share the same regulations, policies, and laws. Table A2 presents the scores of marketization index for the provinces and municipalities obtained from the report by Wang et al. (2017). At a glance, the marketization index is positively correlated with the development level in each region.

Table A2: Marketization Index for Provinces and Municipalities

1	Shanghai	9.5	Fujian	8.0	Hubei	6.5	Hebei	6.0	Yunnan	4.9
2	Zhejiang	9.4	Shandong	7.6	Sichuan	6.5	Heilongjiang	5.6	Ningxia	4.7
3	Jiangsu	9.3	Chongqing	7.2	Hunan	6.3	Hainan	5.4	Guizhou	4.5
4	Guangdong	9.0	Liaoning	7.0	Jiangxi	6.2	Shaanxi	5.2	Gansu	4.0
5	Beijing	8.7	Anhui	6.7	Jilin	6.1	Inner Mongolia	5.2	Xinjiang	3.8
6	Tianjin	8.5	Henan	6.6	Guangxi	6	Shanxi	5.1	Qinghai	3.1

Note: The marketization index is the average from 2005 to 2016 for each province and municipality.

As reported in Table A3, in the new regressions, we replace $SamePro$ with $Institutional.Dist$. The regression results in Columns (2), (3), and (4) show that the coefficients of institutional distance are negative and significant, indicating that institutional distance has a negative effect on intercity co-patent. In Column (4), the coefficient of interaction between HSR connection and institutional distance is negative and significant, suggesting that institutional distance constrains the HSR effect. These results are consistent with one that uses province-border as a measure of institutional distance. They thus confirm that our main thesis regarding the effect of institutional distance remains robust even if we use the marketization index as an alternative measure of institutional distance. The caveat of using the marketization index is that it is a measurement at the provincial level. The political distance between cities of the same province is defined as zeros. So the institutional distance here can be interpreted as a combination of provincial marketization index and province-border definition.

It is worth noting that there's difference between the two definitions. The province-border definition disregards the "quality" of institutions, i.e., it does not measure good or bad institutions; instead, it measures whether organizations in different cities are subject to the same administration and hence similar political, economic, and legal environment. As Hong and Su (2013) noted,

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

Table A3: The Baseline Regression (Using Marketization Index as Institutional Distance)

	Dependent Variable: *CoPatent*			
	(1)	(2)	(3)	(4)
Connect	1.974***	0.006	−0.024	0.243***
	(0.059)	(0.043)	(0.056)	(0.069)
Distance	−0.001***	−0.001***	−0.001***	−0.001***
	(0.0001)	(0.00003)	(0.0001)	(0.00004)
Instutional.Dist	0.028	−1.238***	−1.049***	−1.191***
	(0.074)	(0.038)	(0.050)	(0.045)
$Dist.S_{(0\sim250km)}$			0.406***	
			(0.096)	
$Dist.M_{(250\sim600km)}$			0.003	
			(0.078)	
$Dist.L_{(600\sim1000km)}$			−0.011	
			(0.060)	
$Connect \times Dist.S_{(0\sim250km)}$			0.261***	
			(0.075)	
$Connect \times Dist.M_{(250\sim600km)}$			0.146**	
			(0.073)	
$Connect \times Dist.L_{(600\sim1000km)}$			−0.039	
			(0.070)	
$Connect \times Distance$				−0.00004
				(0.0001)
$Connect \times Instutional.Dist$				−0.165**
				(0.069)
CityPair Controls	No	Yes	Yes	Yes
City&Year FE	No	Yes	Yes	Yes
Observations	79,058	79,058	79,058	79,058
Akaike Inf. Crit.	201,826.100	171,405.200	171,173.400	171,299.200

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors are clustered at the city level.

For Peer Review Only

Chinese local governments prefer to match local firms with universities to form collaboration, so as to keep innovative resources within their territory. They often implement policies and regulations to encourage such local preferences. Under such incentives and expectations, innovative organizations under the administration of the same government are more likely to collaborate with each other. In contrast, the marketization index is a measurement of institutional "quality". A higher score of marketization index is considered an indication of a better institutional setting for organizations to carry out economic activities

1.3 Heterogenous Effect on Cities of Different Sizes

Table A4: Heterogeneous Effect of HSR Connection on Cities of Different Sizes

	Dependent Variable: Co-patent Counts					
	Major-Major		Major-Small		Small-Small	
	(1)	(2)	(3)	(4)	(5)	(6)
Connect	−0.076	−0.060	−0.031	−0.038	−0.035	−0.037
	(0.065)	(0.087)	(0.055)	(0.066)	(0.165)	(0.174)
$Connect \times Dist.S_{(0\sim250km)}$	0.208*		0.226**		0.248	
	(0.111)		(0.094)		(0.206)	
$Connect \times Dist.M_{(250\sim600km)}$	0.094		0.139**		0.175	
	(0.083)		(0.067)		(0.200)	
$Connect \times Dist.L_{(600\sim1000km)}$	−0.038		−0.051		0.074	
	(0.078)		(0.069)		(0.227)	
$Connect \times Distance$		−0.00001		0.00002		0.0001
		(0.0001)		(0.0001)		(0.0001)
$Connect \times SameProv$		0.294**		0.330***		0.266
		(0.120)		(0.089)		(0.183)
City Controls	Yes	Yes	Yes	Yes	Yes	Yes
City, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,350	14,350	49,140	49,140	15,568	15,568
Akaike Inf. Crit.	54,521.920	54,544.550	98,083.250	98,155.330	15,699.140	15,700.630

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors are reported.

To test the heterogeneity of treatment effect among cities of different sizes, we further conduct a subsample analysis on cities of different sizes. We split Chinese cities into two types, major and small cities. Distinguishing between major and small cities can be challenging since there is no official definition of major or small cities in China. Following previous research (e.g. Chen and Fang, 2018) we use the popular five-tier city classification framework that was developed by Yicai Global, a leading media group in China. It ranks cities in accordance with five dimensions of commercial attractiveness, including the concentration of commercial resources, the extent to which a city serves as a business hub, vitality of urban residents, diversity of lifestyle, and future dynamism. It thus classifies 19 cities as first-tier cities, 30 as second-tier cities, and the rest as tier 3 to tier 5. Following this classification, we define the first and second-tier cities as major cities, and the rest as small cities. There are a total of 49 major cities, and 236 small cities. To disentangle the effect of HSR, we separate the observations into three types: major-major, major-small, and small-small. We run sub-sample regressions of the three types of city-pairs. Table A4 reports the HSR effects on city-pairs of different size combinations. The analysis reveals three additional intriguing results. First, the most significant HSR effect comes from between major-small city-pairs. HSR connection increases the number of co-patents by 22.6% within 250 km, 13.9% within 600 km, and 33% within the same province for the major-small city-pairs. Second,

For Peer Review Only

for large-large city-pairs, the significant HSR effect (20.8 % increase) is only found within 250 km, and the effect is more pronounced (29.4% increase) within the same province. Third, HSR connection has no effect on innovation collaborations in small-small city-pairs.

1.4 Instrument Variable Regression

Our results may be affected by endogeneity that may occur as a result of missing variables or reverse causality. As we have included city and year fixed effect and a number of control variables in our regressions, endogeneity due to missing variables should not be a concern but reverse causality can be. This is because policymakers in China may have planned the HSR network to connect cities with the high potential of future economic connection. If that is the case, the endogeneity problem could create upward bias and the estimates could be spurious. One way to tease out the endogeneity is to use instrument variable, which correlates with the endogenous variable HSR connection but does not directly correlate with the outcome variable, intercity co-patents. Such variables are surely difficult to find. We follow the literature and use two instrument variables, historic rail connection, and city altitude (Baum-Snow et al., 2017; Dong et al., 2019). Historic rail connection is closely correlated to the modern-day HSR layout but is arguably not directly correlated with intercity innovation collaboration today, as Baum-Snow et al. (2017) argued the old rail system served very different functions, such as shipping raw materials and manufactures between larger cities and to provincial capitals according to the dictates of national and provincial annual and five-year plans. We use the Chinese rail system in 1961 as the first instrument variable of modern-day HSR network. The second instrument is geographical elevations of cities; due to the construction cost, cities with higher altitudess are less likely connected to the HSR network.

Table A5: The First Stage Regression of 2SLS

	Dependent variable:
	connect_2018
Elevation.l	-0.00003 (0.00002)
Elevation.s	-0.0002^{***} (0.00001)
Historic.l	0.183^{***} (0.018)
Histroic.s	0.128^{***} (0.012)
Observations	5,647
R^2	0.158

Note: This is the first stage regression of 2SLS. The endogenous variable "connect2018" is regressed on all the instrument variable and exogenous variable. In this table, we only show the coefficients of the four instrument variables.

Due to that the IVs are time-invariant—that is, the instruments can only predict whether

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

cities are connected by 2018 but not when—we use a long-difference model to examine the effects of HSR-connection on intercity innovation collaboration. The long-difference model converts the panel data into a cross-sectional one by taking the logarithmic difference of co-patent count between 2005 and 2018[1]. The first stage is to regress the endogenous variable, $Connect_{ij}$, on the instrument variable and exogenous variable as shown in Table A5.

Due to the dyadic nature of our observation, each observation involves two cities. Each two cities are arranged in their GDP size and defined as the larger or smaller city, as indicated by the suffix ".L" and ".S". The first stage result shows that for the larger city, elevation does not predict the HSR connection in 2018 while the elevation of smaller cities is negatively correlated with the prospect of HSR connection. That means the policymaker has planed the HSR network to connect the larger cities regardless of the geographical condition, while a harsh geographical environment could impede the HSR connection for the smaller cities. Historical rail connections positively predict the modern-day HSR connection for both smaller and larger cities. Geographical elevation and historic connection are strong instruments as indicated by the significant coefficients.

Table A6: The Long Difference OLS and IV regression Results

	Dependent variable:			
	Copatent count (2005-2018)		Collaboration partners (2005-2018)	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
$Connect$	0.151*** (0.049)	−0.040 (0.191)	0.092*** (0.036)	−0.130 (0.139)
$Connect \times Dist.S_{(0\sim250km)}$	0.310*** (0.104)	0.655** (0.300)	0.207*** (0.076)	0.433** (0.218)
$Connect \times Dist.M_{(250\sim600km)}$	−0.126 (0.078)	0.173 (0.229)	−0.092 (0.057)	0.083 (0.166)
$Connect \times Dist.L_{(600\sim1000km)}$	−0.088 (0.079)	0.077 (0.219)	−0.010 (0.057)	0.207 (0.159)
Observations	5,647	5,647	5,647	5,647
R^2	0.246	0.243	0.276	0.271

Note: The table compares the OLS and IV regression results. It only presents the endogenous variables.

Table A6 reports the 2SLS long-differecnce regerssion results. Columns (1) and (2) show the effects on intercity co-patent count and Columns (3) and (4) are on collaborative partnerships. Column (1) presents the OLS results and it shows that co-patents in city-pairs that are HSR-connected tend to grow by 31% for cities within 250 km. For city-pairs that are beyond that range, they expect to grow by 15.1% in co-patents. This finding closely aligns with our previous results using Negative Binomial panel regression. Column (2) shows the IV 2SLS results, where the standard errors are inflated as expected. The coefficient of HSR connection within 250km remains

[1]To implement a Two-Stage Least Square approach means we cannot have Negative Binomial regression. So instead we use OLS and take the logarithmic of the outcome variable. Following Dong et al. (2019), because there are many zero we use log(x + 1) method.

For Peer Review Only

significant and changes to 0.655, suggesting that the IV result generates an unbiased estimate higher than the OLS result. The same applies to collaborative partners, the HSR effect increases from 0.207 in OLS estimate to 0.433 IV estimate. Higher IV estimates echo Dong et al.'s (2019) research, where they also find higher IV coefficients than OLS estimates using historic and urban geographics as an instrument for HSR connection. The interpretation could be that policymakers preferred equitable development and planned the HSR to connect less developed cities. Again, the IV regression results reaffirm the robustness of our findings, confirming that our main results are not subject to the influence of endogeneity in terms of upward bias.

For Peer Review Only

References

Baum-Snow, Nathaniel, Loren Brandt, J Vernon Henderson, Matthew A Turner, and Qinghua Zhang, "Roads, railroads, and decentralization of Chinese cities," *Review of Economics and Statistics*, 2017, *99* (3), 435–448.

Bin, Peng, Xiaolan Chen, Andrea Fracasso, and Chiara Tomasi, "Firm employment growth in China: The role of marketization and regional economic factors," *Growth and Change*, March 2020, *51* (1), 402–439.

Chen, Gongmeng, Michael Firth, Daniel N Gao, and Oliver M Rui, "Ownership structure, corporate governance, and fraud: Evidence from China," *Journal of corporate finance*, 2006, *12* (3), 424–448.

Chen, Yang and Zheng Fang, "Industrial electricity consumption, human capital investment and economic growth in Chinese cities," *Economic Modelling*, 2018, *69*, 205–219.

Dong, Xiaofang, Siqi Zheng, and Matthew E Kahn, "The Role of Transportation Speed in Facilitating High Skilled Teamwork Across Cities," *Journal of Urban Economics*, 2019, p. 103212.

Firth, Michael, Chen Lin, Ping Liu, and Sonia M L Wong, "Inside the black box: Bank credit allocation in China's private sector," *Journal of Banking & Finance*, 2009, p. 12.

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

Li, Hongbin, Lingsheng Meng, and Junsen Zhang, "Why Do Entrepreneurs Enter Politics? Evidence from China," *Economic Inquiry*, July 2006, *44* (3), 559–578.

Mao, Qiliang and Xianzhuang Mao, "Cultural barriers, institutional distance, and spatial spillovers: Evidence from regional industrial evolution in China," *Growth and Change*, July 2021, p. grow.12527.

Wang, Xiaolu, Gang Fan, and Jingwen Yu, "Marketization index of China's provinces: NERI report 2016," *Social Sciences Academic Press: Beijing, China*, 2017.

For Peer Review Only

Revise and Resubmit

To editor

We would like to thank you and three reviewers for the insightful and constructive comments and the opportunity to revise this paper. We have taken on board all these suggestions and revised the paper accordingly. We appreciate that the comments have helped improve the paper. The following summarizes the major points of our response and revision.

- In response to Reviewer 1, we have used the marketization index as a proxy for institutional distance and run new regressions. The results are consistent with one that uses province borders as a measure. We explained why the marketization index differs from the "provincial-border" measure of institutional distance, and why the province-border measure fits better to the purpose of our research.
- To Reviewer 2, we have largely rewritten the introduction section in order to clarify the research gaps our study aims to fill and the contributions it makes. We have also removed three original hypotheses (i.e. Hypothesis 1a Total intercity innovation collaboration between City A and B decreases in relation to the distance between them, Hypothesis 2a Institutional friction decreases intercity innovation collaboration, and Hypothesis 3a Geographical friction decreases II collaborations more than URI collaborations; institutional friction reduces URI collaborations more than II collaborations). The removal of these hypotheses allows us to focus on the HSR-induced effect and thus makes the focus of our paper sharper. Further, we have tested the endogeneity problem using long-difference instrument variable and conducted sub-sample analysis highlighting the heterogeneity of the HSR effect among cities of different sizes.
- To Reviewer 3, we explained the common trend issues, included additional control variables following his/her advice.

To make our revision more readable, we have highlighted our response in red color. We remain available to respond to any additional queries.

For Peer Review Only

Reviewers 1

The paper tried to answer some key questions: whether HSR improves intercity innovation collaboration, how HSR affects various innovative actors such as firms, universities, and research institutes differently in intercity innovation collaboration, and, how HSR affects innovation collaboration between cities of different sizes. The paper did a good job and qualified to publish in this journal.

One small question is: how to measure the formal institutions which comprise of political, economic, and legal rules (including protection of IPR) and informal institutions. It tried to answer these questions in hypotheses 2 and 3, such as 2a: Institutional friction decreases intercity innovation collaboration. In the paper, it only used the provincial border (same province) to test the institutional factor. I think this is not a good measure. In fact, some regions such as Shanghai, Zhejiang, and Jiangsu have similar formal and informal institutional arrangements. This can also apply to the Northeast region. Previously, many papers used the index of marketization to test the institutional differences across different provinces. I think it is best to try this index.

We appreciate your confirmation on the merits of our research. Thank you also for suggesting an alternative measure of institutional distance. We are aware that the marketization index is a frequently used measure of institutional quality in empirical research on Chinese institutional environments (Chen et al., 2006; Li et al., 2006; Firth et al., 2009). The index indicates the extent to which Chinese provinces progress toward a fully-fledged market economy under economic reform (Bin et al., 2020). The index is composed of five pillars that reflect the different aspects of the marketization process, namely development of intermediate organization and law, government-market relation, private economic development, product market development, and factor market development.Wang et al. (2017) A province's score in the marketization index is the aggregate score of all sub-indices in five pillars. MI was developed by the National Economic Research Institute (NERI), an influential think tank in China, and the first MI report was published in 2000. We use this measure and run new regressions. Following Mao and Mao (2021), we calculate the intercity institutional distance by using the five marketization index dimensions put together by Wang et al. (2017) using the following equation:

$$Institutional.Dist = \sum_{k}^{5} [(I_{k,i} - I_{k,j})^2 / V_k] / 5 \tag{1}$$

where $I_{k,i}$ is the marketization index k for city i, V_k is the variance of institutional score of kth dimension . As the marketization index is measured at the provincial level, we additionally define Institutional distance between cities of the same province is zero because cities in the same province tend to share the same regulations, policies, and laws. Table 1 presents the scores of the marketization index for the provinces and municipalities put together by Wang et al. (2017).

For Peer Review Only

Table 1: Marketization Index for Provinces and Municipalities

1	Shanghai	9.5	Fujian	8.0	Hubei	6.5	Hebei	6.0	Yunnan	4.9
2	Zhejiang	9.4	Shandong	7.6	Sichuan	6.5	Heilongjiang	5.6	Ningxia	4.7
3	Jiangsu	9.3	Chongqing	7.2	Hunan	6.3	Hainan	5.4	Guizhou	4.5
4	Guangdong	9.0	Liaoning	7.0	Jiangxi	6.2	Shaanxi	5.2	Gansu	4.0
5	Beijing	8.7	Anhui	6.7	Jilin	6.1	Inner Mongolia	5.2	Xinjiang	3.8
6	Tianjin	8.5	Henan	6.6	Guangxi	6	Shanxi	5.1	Qinghai	3.1

Note: The marketization index is the average score of five pillars over the period of 2005 to 2016 for each province and municipality.

For Peer Review Only

Table 2: The Baseline Regression (Using Marketization Index as Institutional Distance)

	Dependent Variable: *CoPatent*			
	(1)	(2)	(3)	(4)
Connect	1.974***	0.006	−0.024	0.243***
	(0.059)	(0.043)	(0.056)	(0.069)
Distance	−0.001***	−0.001***	−0.001***	−0.001***
	(0.0001)	(0.00003)	(0.0001)	(0.00004)
Instutional.Dist	0.028	−1.238***	−1.049***	−1.191***
	(0.074)	(0.038)	(0.050)	(0.045)
$Dist.S_{(0\sim250km)}$			0.406***	
			(0.096)	
$Dist.M_{(250\sim600km)}$			0.003	
			(0.078)	
$Dist.L_{(600\sim1000km)}$			−0.011	
			(0.060)	
$Connect \times Dist.S_{(0\sim250km)}$			0.261***	
			(0.075)	
$Connect \times Dist.M_{(250\sim600km)}$			0.146**	
			(0.073)	
$Connect \times Dist.L_{(600\sim1000km)}$			−0.039	
			(0.070)	
$Connect \times Distance$				−0.00004
				(0.0001)
$Connect \times Instutional.Dist$				−0.165**
				(0.069)
CityPair Controls	No	Yes	Yes	Yes
City&Year FE	No	Yes	Yes	Yes
Observations	79,058	79,058	79,058	79,058
Akaike Inf. Crit.	201,826.100	171,405.200	171,173.400	171,299.200

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors are clustered at the city level.

As reported in Table 2, in the new regressions, we replace *SamePro* with *Institutional.Dist*. The regression results in Columns (2), (3), and (4) show that the coefficients of institutional distance are negative and significant, indicating that institutional distance has a negative effect on intercity co-patent. In Column (4), the coefficient of interaction between HSR connection and institutional distance is negative and significant, suggesting that institutional distance constrains the HSR effect. These results are consistent with one that uses province-border as a measure of institutional distance. They thus confirm that our main thesis regarding the effect of institutional distance remains robust even if we use the marketization index as an alternative measure of institutional distance. The caveat of using the marketization index is that it is a measurement at the provincial level. The political distance between cities of the same province is defined as zeros. So the institutional distance here can be interpreted as a combination of provincial the marketiztion index and province-border definition.

It is worth noting that there's difference between the two definitions. The province-border definition disregards the "quality" of institutions, i.e., it does not measure good or bad institutions; instead, it measures whether organizations in different cities are subject to the same administration and hence similar political, economic, and legal environment. As Hong and Su (2013) noted, Chinese local governments prefer to match local firms with universities to form collaboration, so as to keep innovative resources within their territory. They often implement policies and regulations to encourage such local preferences. Under such incentives and expectations, innovative organizations under the administration of the same government are more likely to collaborate with each other. In contrast, the marketization index is a measurement of institutional "quality". A higher score of marketization index is considered an indication of a better institutional setting for organizations to carry out economic activities

In our paper, we test how institutional proximity, under the same provincial administration, affects intercity innovation collaboration and moderates the HSR effect. We compare how institutional factor affects URI and II collaboration differently based on the argument that university and research institutes (URI) are closely associated with the local government and hence are more constrained by institutional distance. So, our argument is not based on institutional "quality", and the province-border binary variable is easier to interpret the results. Therefore, we keep the province-border measure in our main paper (Hong and Su, 2013; Chen et al., 2019).

(Due to the journal's strict 10,000 words limit, we only sum up the results in the main text and leave the details of methodology and results in the online Appendix file.)

For Peer Review Only

Reviewer 2

This paper discusses the role of HSR connections on interurban co-patent intensity. Overall, this paper is well-written. The authors use a substantial analysis of data and reveal some fine-grained results, the methodology seems sound and valid. I think most of my concerns relate to clarifications/qualifications that could be made as the paper moves along.

1) This is not a very original idea. The relation between collaboration intensity and geographical distance/institutional proximity/infrastructures is widely and intensively discussed in the literature on innovation geography, albeit it perhaps has not been examined through a formal econometric way. The authors should refer to some of the most cited work on innovation geography, like Ponds et al. (2007, 2009), Anderson et al. (2014), Katz (1994), etc., and some of the work in geography journals in China.

For Peer Review Only

Thanks for the comment and suggestion. We agree with the reviewer that the literature on the relation between collaboration intensity and geographical distance/institutional proximity/infrastructure is mature. Yet, our review of literature also indicates the scope for research that provides a more nuanced understanding of the relation. We highlight two particular areas. One is the effect of changes in infrastructure on the relation. Another is the relation under the decentralization system in China. We have largely rewritten the introduction section in order to provide greater clarity of the research novelty in our study. Hence, the contributions of our paper are three-fold. First, we enrich the literature on geographical proximity and innovation collaboration by unraveling the HSR-mitigated differential effect of geographic friction on the quantity and quality of inter-city innovation collaborations. Second, we draw on a regional decentralization perspective to explore how institutional proximity moderates the HSR effect. Thus, we enrich the literature by providing a more nuanced understanding of how different dimensions of proximity interact to affect intercity innovation collaboration. Third, we again follow the decentralization perspective to explore whether the HSR effect is more constrained in geographical distance for II collaboration and more constrained in institutional distance for URI collaboration. Our research, therefore, sheds new light on how different types of innovation actors with varying inherent incentives and behaviors may respond differently to the improved transportation infrastructure and manifest themselves differently in intercity innovation collaboration.

2) The "intercity" and "interregional" are confusing throughout the paper, it should be kept consistent.

Thanks for the comment and suggestion. We have followed your suggestion and used "intercity" to keep it consistent throughout the paper.

3) I am confused how many cities are in the datasets? All Chinese cities or only the cities along the railway? How the geographical distance be measured? R geosphere is not clear enough — is it direct distance between cities or the actual railway distance? These could be influential to the models and results.

Thanks for the comments and questions. First, there were 293 prefecture cities and 4 municipalities in China in 2018. We only consider the cities that had intercity co-patents and exclude those without, which leaves us a total of 285 prefectures and municipalities in the dataset. We have revised the paper to point this out in the data section on page 7.

Second, geographical distances are measured in straight-line (or Euclidean) distance between cities using geographical information. R geosphere package is used to calculate the straight-line distance based on the longitude and latitude of cities. We did not use the actual railway distance because not all city-pairs are HSR-connected during the sample periods, as it would not be possible to measure the actual rail distance between city-pairs without an actual rail connection. As there are two "differences" in the DID method, one "difference" is the timing of treatment and the other is whether observations are treated or not. The control groups contain city-pairs that are never HSR-connected, so we cannot measure the rail distance between cities that do not exist.

As Marek et al. (2017) have found both straight-line distance and travel time have been used in the literature to measure geographical distance, but these two measures do not generate results of significant differences. Actually, most studies prefer to use straight-line distance due to its relatively low-cost, especially for many dealing with the gravity model of international and regional studies (Scherngell and Hu, 2011; Marek et al., 2017). We revise the paper to explain it more clearly on Page 7.

4) There might be potential multicollinearity among the independent variables, i.e., same province, geographical distance and HSR. Cities in a same province are arguably closer to each other, and are easier to be connected by HSR. I did not see any diagnostics and statements. The signs of significant multicollinearity can be seen in the statistics summary.

Thanks for your comment. As can be seen from the correlation analysis in Table 2, most correlation coefficients are within reasonable ranges. There exists high correlations between dependent variables, such as 0.99 correlation coefficient between $CoPat$ and $CoPatW$, and between control variables, such as 0.89 between $SinglePatent.L$ and $GDP.L$. However, high correlations among these variables are expected and do not constitute a multi-collinearity problem. First, a high correlation between dependent variables is not an issue because they are not included in the same regression model. Second, a high correlation between variables only becomes a problem when the interest is to identify the coefficients of such variables (Greene, 2012, page 89). Hence high correlations among control variables are innocuous because 1). it does not interfere with the

For Peer Review Only

coefficient estimates of major independent variables, and 2). the coefficients of control variables are not the concern.

The major concern may come from correlations between independent variables, such as between geographical distance and institutional distance (i.e. whether or not both belong to the same province). There is certainly a correlation between the two, as cities of close distance tend to belong to the same distance, but this is not always the case. For instance, cities on the province borders may be geographically proximate to cities of other provinces. Moderate correlation not only is innocuous but is the exact reason to control these variables, because excluding these variables results in missing variable biases (Angrist and Pischke, 2008). In Column (4) in Table 4, controlling geographical distance is necessary because otherwise the distance effect would be subsumed into the institutional proximity effect, causing missing variable bias.

To test multicollinearity, we inspected the variance inflation factors (VIFs) of the variables using linear regression (the convention is to use linear regression when the main regression model is non-linear). The VIFs value for *Connect*, *SamePro*, and *Distance* are respectively 5.1, 1.66 and 1.68 , which are below the acceptable level of 10 (Neter et al., 1996).

To address concerns of multicollinearity, we have included an explanation on page 10.

5) There might be potential endogeneity between intercity collaboration and HSR connection. Big cities always have more collaboration and HSR connections and vice versa. The endogeneity issues should be mentioned and tested.

Thanks for your comment. In the DID regression, we have included city and year fixed effect and a number of control variables. So endogeneity due to missing variables should not be a concern, but reverse causality can be. This is because policymakers in China may have planned the HSR network to connect cities with the high potential of future economic connection. If that is the case, the endogeneity problem could create upward bias and the estimates could be spurious.

To address this concern, we follow Baum-Snow et al. (2017) and Dong et al. (2019) and use two instrument variables, historic rail connection and city altitude. Historic rail connection is closely correlated to the modern-day HSR layout but is arguably not directly correlated with intercity innovation collaboration today, as Baum-Snow et al. (2017) argued the old rail system served very different functions, such as shipping raw materials and manufactures between larger cities and to provincial capitals according to the dictates of national and provincial annual and five-year plans. We use the Chinese rail system in 1961 as the first instrument variable of the modern-day HSR network. The second instrument is geographical elevations of cities; due to the construction cost, cities with higher altitudes are less likely connected to the HSR network.

Due to that the IVs are time-invariant—that is, the instruments can only predict whether cities are connected by 2018 but not when—we use a long-difference model to examine the effects of HSR-connection on intercity innovation collaboration. The long-difference model converts the

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk
For Peer Review Only

panel data into a cross-sectional one by taking the logarithmic difference of co-patent count between 2005 and 2018. Results as reported in Appendix Table A5 show that similar to Dong et al. (2019), the HSR effect remains positive and significant. The HSR effect size is actually even larger in the IV regression, suggesting that our DID estimates can be explained as the lower bound of the HSR effect. It is possible that Chinese policymakers intentionally select the less-developed cities to connect to the HSR network. The IV regression results reaffirm the robustness of our findings, confirming that our main results are not subject to the influence of endogeneity.

6) The authors discuss the URI collaboration and II collaboration. How about the U-U, U-R, U-I and R-I collaboration? It is odd that there are no clarifications why the authors ignore these types of collaboration, which are also important in co-invention activities.

Thanks for your comment. In the study, we define URI collaborations as those involving either universities or research institutes. Hence, URI collaborations include all the U-U, U-R, U-I, and R-I co-patents. We add an explanation in a footnote on Page 6 :

"URI collaborations include university-university (UU), university-research institutes (UR), university-industry (UI), and research institute-industry (RI). Any co-patents involving universities or research institutes are categorized as URI collaborations."

7) The institutional proximity may not only refer to the differences of institutional setting between different provinces. It also can refer to the institutional differences among organizations, e.g., Ponds et al. (2007). So, the discussion on URI or II collaboration makes me think of another dimension of institutional proximity, which is a bit confusing and distractive. These conceptual differences of institutional proximity in different contexts should be mentioned and distinguished in the paper.

Thanks for your comment. The definition of various sorts of proximity in the literature evolves over time and sometimes differs slightly from one author to another. For Institutional proximity, as Balland et al. (2015) noted, there are two main definitions. The first definition refers to the degree to which organizations share similar values and norms at the macro-level (Boschma, 2005), and the second regards actors operating in the same subsystem within academia, industry, or government (Etzkowitz and Leydesdorff, 2000; Ponds et al., 2007). The two definitions are distinctive to a certain degree. The first definition emphasizes the institutional setting at a macro-level, such as countries and regions, and organizations belong to the same institutional setting are considered institutionally proximate, whereas the second stresses whether organizations belong to the same type, such as firms, universities and such (Ponds et al., 2007). That is, according to Ponds et al. (2007), firms are institutionally proximate to other firms but distant to universities or government organizations because different types of organizations are subject to different incentives.

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk
For Peer Review Only

Our definition of institutional proximity follows the first one, that is, organizations under constraints of similar rules and norms. We adopt a province-border measurement of institutional distance, similar to Hong and Su (2013), where cities that belong to the same province are institutionally proximate and vice versa. Hence, our definition of institutional proximity differs from Ponds et al. (2007). Then, in the further analysis, we explore how HSR network affects URI and II collaboration differently. The differentiation of URI and II collaboration is aimed to explore the heterogeneous effect of HSR connection, which has nothing to do with Ponds et al.'s (2007) definition of institutional proximity.

Thanks again for pointing that out. We've explained all this in the main text.

8) The variable HSR is a binary one, which obviously ignores the volume/intensity (like numbers of trains or passenger flows) of the intercity exchange by HSR. Incorporating this analysis could be exhaustive, but the authors should clarify why the choice of a binary variable is better.

Thanks for your comment. Apart from issues such as exhaustion of analysis and possible unavailability of data, there are two further reasons why we stick to the binary variable. First, easier interpretation—using binary variables we can interpret the results as treatment effect of HSR connection between cities. Especially when the key variable interacts with other variables, a continuous variable such as volume can be difficult to interpret. Second, the HSR effect is unlikely to be linear in relation to the volume and numbers of trains.

For these reasons, we did not use the volume/intensity variable in the regressions. We now revise our paper to explain our choice of the HSR measure more clearly on Page 10

9) The authors use a longitudinal approach which is good. However, what I really expect to know is to what extent the HSR influences the collaboration intensity after the cities being connected to the networks (which I think is the issue at the heart of this study)? Frankly, I care much less about the "sighs" or the "overall impact" of the relationship between HSR and collaboration, because it is only a present and average effect (based on the regressions). I am much more concerned about the elasticity or margins of the impacts of the HSR on collaboration for different sizes/types of cities, before and after the connections. There are lots of evidence show that the smaller cities may not always benefit from the HSR, as the talents and other innovation related resources will be taken away by the HSR. I did not see any description on this. The authors should address this carefully.

Thanks for your comment. The reviewer's question is concerned with the heterogeneity of treatment effect among cities of different sizes. To respond, we have conducted a subsample analysis on cities of different sizes and partially reported the results in the robustness section (Due

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

For Peer Review Only

to words limitation, we include the whole analysis in the online Appendix).

We split Chinese prefecture cities into two types, major and small cities. Distinguishing major and small cities can be challenging since there is no official definition of major or small cities in China. Simply using GDP or total patents as a measurement may be biased and may ignore some other essential factors that impact the prominence of cities. Following previous research (e.g. Fang et al., 2017; Chen and Fang, 2018), we use the widely-adopted five-tier city classification framework in our approach. This framework was developed by Yicai Global, a leading media group in China. It ranks cities in accordance with five dimensions of commercial attractiveness, including the concentration of commercial resources, the extent to which a city serves as a business hub, vitality of urban residents, diversity of lifestyle, and future dynamism It thus classifies 19 cities as first-tier cities and 30 second-tier cities, and the rest were classified as tier 3 to tier 5. Following this classification, we define the first and second-tier cities as major cities, and the rest as small cities. There are a total of 49 major cities, and 236 small cities, as illustrated in Online Appendix Figure A1 in the paper. In dealing with dyadic city-pairs, we separate the observations into three types: major-major, major-small, and small-small. We run sub-sample regressions of the three types of city-pairs.

Table 3: Heterogeneous Effect of HSR Connection on Cities of Different Sizes

	Dependent Variable: Co-patent Counts					
	Major-Major		Major-Small		Small-Small	
	(1)	(2)	(3)	(4)	(5)	(6)
Connect	−0.076	−0.060	−0.031	−0.038	−0.035	−0.037
	(0.065)	(0.087)	(0.055)	(0.066)	(0.165)	(0.174)
$Connect \times Dist.S_{(0\sim250km)}$	0.208*		0.226**		0.248	
	(0.111)		(0.094)		(0.206)	
$Connect \times Dist.M_{(250\sim600km)}$	0.094		0.139**		0.175	
	(0.083)		(0.067)		(0.200)	
$Connect \times Dist.L_{(600\sim1000km)}$	−0.038		−0.051		0.074	
	(0.078)		(0.069)		(0.227)	
$Connect \times Distance$		−0.00001		0.00002		0.0001
		(0.0001)		(0.0001)		(0.0001)
$Connect \times SameProv$		0.294**		0.330***		0.266
		(0.120)		(0.089)		(0.183)
City Controls	Yes	Yes	Yes	Yes	Yes	Yes
City, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,350	14,350	49,140	49,140	15,568	15,568
Akaike Inf. Crit.	54,521.920	54,544.550	98,083.250	98,155.330	15,699.140	15,700.630

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors are reported.

Table 3 reports the HSR effects on city-pairs of different size combinations. Columns (5) and (6) report the results on small-small city-pairs, and both show the weak significance of HSR connection on innovation collaborations. The most significant HSR effect comes from between major-small

For Peer Review Only

city-pairs. HSR connection increases co-patents by 22.6% within 250 km, 13.9% within 600 km, and 33% within the same province for the major-small city-pairs. As for large-large city-pairs, there is a 20.8 % increase within 250 km, and an insignificant effect within 600 km, and 29.4% within the same province.

For Peer Review Only

Reviewer 3

This article addresses a highly important topic related to the role of infrastructure in fostering innovation through an increase in collaborative innovation effort. Authors use a gravity model to analyze the effects of the introduction of the High-Speed Rail (HSR) (and other variables) on collaborative innovation output (in the form of co-patents filed by researchers/inventors based on both sides of the connected city pairs), whereby high-speed connections between city pairs are considered to bridge the distance (cost reduction? reduction of traveling time, safety) and increase collaboration outcomes relative to what it would have been in their absence. The introduction of HSR connectivity is presented as a natural experiment. This study, therefore, uses double-distance approach to perform a form of impact evaluation of HSR impact on innovation collaboration. The actual impact that the evaluation is attempting to measure is based on the counterfactual representing the difference between actual innovation-collaboration outcomes after HSR connection and what the outcome would have been if the HSR connection had not been installed, all other things following their pre-existing trends.

Although difference in difference is an accepted methodology for assessing impact in a natural experiment, its application to this case with the inclusion of a very limited number of control variables (Total single-applicant patents for City i in year t, Total gross production in millions, Government expenditure in science and technology in millions, Total highway ridership in thousands, Total mobile phone users in thousands) exposes the estimated results to a substantial omitted variables bias (Ravallion, 2001) and does very little to deal with the heterogeneity, not only of the city pairs under analysis, but also of the actual firms and research institutions involved in those collaborative efforts, as well as the particular characteristics of researchers and inventors who engage in the corresponding collaborative activities (Maietta, 2015). Double difference is also not robust to reverse causality (what if HSR connections were primarily established between cities with characteristics expected to foster more intensive collaboration?) and heteroscedasticity in the covariates (See Ravallion, 2001, among others). I therefore wish to make the following observations that may contribute to improving the methodological approach and reduce the estimation bias:

1). Geographical distance as a determinant of research and innovation collaboration, which forms the main thrust of this study, is only one of the numerous factors used in the literature and is far from being the most important, as shown in Jeong et al (2011) and Maietta (2015) among others. Its role is recognized as very important in fostering face-to-face communication and informal communication, therefore indispensable for exchange of tacit knowledge. But this does not imply that it should take the most prominent role in the outcome of research collaboration at the expense of other equally important factors. In some studies, such as Maietta (2015), geographical distance can become insignificant as a predictor for research collaboration if many more relevant covariates are included in the prediction model.

For Peer Review Only

Thanks for your comment. We agree that geographical distance is only one of the factors that influence research collaboration. However, it is still an important one. For instance, Maietta's (2015) very interesting research shows that product innovation in agricultural-food companies is positively affected by geographical proximity to a university, even though there is no effect of geographical proximity to a university on collaborations with universities after controlling for the same set of variables. Despite the inconsistent results, Maietta (2015) concluded that knowledge spillovers from local universities can be important because a firm within a radius of 150 km from a university has a higher likelihood of product innovation than does a more distant firm. Research such as Maietta (2015) suggests that the effect of geographical distance is not a foregone conclusion. A strength of our study is that we bridge one stream of study on proximity and another on infrastructure and innovation to unravel the differential effect of the HSR-mitigated effect of geographical distance and institutional distance on innovation. We also use a complete set of co-patent data covering all industries that are constructed in dyadic observation. So, we shed new insights on the issue under investigation. To explain more clearly the research problem, we have largely rewritten the introduction section. In the following excerpt, we hope we have placed our research in a clearer context.

"Inter-city innovation collaborations need to overcome geographic friction. Early research (e.g. Maurseth and Verspagen, 2002; Fischer et al., 2006) that followed Jaffe et al.'s (1993) seminal work found a substantial influence of geographical proximity on innovation collaboration. However, later research that embraced Boschma's (2005) fivefold classification of proximity as an analytical framework has produced the more balanced findings. Firstly, geographical proximity is found to be less influential than previously assumed once non-geographical forms of proximity are considered in innovation collaboration (Torre and Rallet, 2005; Boschma, 2005; Balland et al., 2015). Secondly, geographical and non-geographical forms of proximity are often found to be positively correlated (Balland et al., 2015). Nonetheless, geographical proximity is still found to positively influence the formation of innovation collaboration when other forms of proximity are included in studies (Scherngell and Hu, 2011; Balland, 2012; Hong and Su, 2013; Lata et al., 2015; Marek et al., 2017; Cao et al., 2019). "

2). In addition, co-patent applications represent the outcome of collaborative efforts rather than the efforts themselves, whose rate of success depends again on multiple factors. The outcome may take time to materialize between the actual period of increase in collaboration and the final development of the resulting patented invention. This fact is recognized by the authors in the limitation section. It may therefore be more useful to have separate estimations: one relating the effects of reduction in travelling costs and time relative to other transportation alternatives linking the city pairs (air link, highway, regular train connection) along with other factors presented in the literature (see below) to the actual engagement in research collaboration, and another relating the

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

increase in actual engagement in collaborative efforts (along with other relevant covariates) to the innovation outcomes . From this study it is unclear what the actual cost and time savings are with respect to alternative connection means, which may represent the real driver of increased travelling between the city pairs. Measuring collaboration through co-patent applications also leaves out many collaborative structures that do not necessarily lead to patents, but have nonetheless a positive contribution to the innovation outcomes.

Thanks for the comment. We agree with the reviewer that more collaborative efforts do not necessarily generate more collaborative results, as projects can succeed and fail due to random factors. Hence, collaborative efforts and results are not completely equivalent. But we argue that they are closely related because the former is a good proxy for the latter due to the law of large numbers. Cities contain thousands of firms and other innovative actors. Due to the law-of-large-number, we believe co-patent applications can be a good measurement of collaborative innovation. Moreover, the measurement error in the dependent variable can be absorbed into the error term without causing biases to the coefficient estimates. Also co-patents are widely used measure of innovation collaboration, such as in works by Sun and Cao (2015), Bergé et al. (2017), and Marek et al. (2017).

We appreciate the reviewer's suggestion on breaking down the study and separately analyzing how HSR save traveling cost and how improved collaboration effort leads to better innovation outcome. However, quantifying the extent to which HSR saves travel costs as compared with other transport alternatives can be challenging. Cost may need to be measure not just by how much people pay for the journey (absolute cost) but also by how quickly people can move from A to B (cost relative to travel speed). Collecting all cost information, if available, can be time-consuming and costly. Though we don't know exactly how much HSR has reduced people's travel costs, we do know HSR has substantially changed the way people travel in-between cities (Haixiao and Ya, 2019). Evidence like this suggests that people see HSR as a value-for-money mode of transport. How improved intercity research collaboration improve innovation outcome is another interesting and worthy topic for academic inquiry. As most collaboration studies are carried out at the organizational level, this topic could bring more insights into the effect of innovative collaboration on a larger scale. But these two issues are beyond the scope of this study and can be areas for future research. We include the two questions in the potential extensions section on page 19.

Lastly, we agree with the reviewer that measuring innovation collaboration leaves out many collaborative innovations that do not result in patents. Acknowledging that not all innovations lead to patents, the literature nonetheless heavily relies on patents to measure innovation because patents are the most tractable and available source at a large scale for measuring innovation.

3). The use of difference in differences is predicated on the assumption of common support

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk
For Peer Review Only

between treatment group and the non-treated, as well as common trends over the period of analysis. The trends displayed in figure 4 clearly indicate a divergence between HSR-connected cities and the comparison group as early as t-2, which makes double differences inadequate. No analysis of common support is provided, while it is indispensable for the consistency of the corresponding estimates (see Heckman et al., 1998). Failure to ensure common support and similarity in initial conditions between the treatment and the comparison group in a major source of bias when applying difference in differences (Ravallion, 2001).

Thanks for your comment. The common trend (or common support) assumption is the foundation of DID analysis. If the common trend assumption is violated, then the DID estimates can be biased because the estimate captures not only the HSR effect but also the trend effect. We agree with the reviewer that in Figure 4, there is a slight and visible divergence between the treated and control groups, especially at the t-1 period. But we argue that a perfect common trend is improbable because all the variables are random, and randomness inevitably creates deviation from a perfect common trend. That's why we carry out placebo tests and an event study to check whether the deviation from a perfect common trend is statistically tolerable.

In Figure 5 of the event study, we show that from t-4 to t-1, the common trend generally holds. That is, the treatment effect before the actual treatment is statistically insignificant. It is noticeable that in period t-1, though insignificant, the effect "jumps up" right before the actual HSR connection. Our interpretation is that organizations may move ahead to carry out more collaborative activities in anticipation of HSR connection. As R&D and innovations are long-term projects, it is likely that in the foresight of better connectivity and more convenient travel, firms move ahead to increase collaborations with partners that are more accessible in the near future. The "step-ahead" effect could be the reason for the slight divergence before the actual HSR connection. In the right panel of Figure 5, there exists no "step-ahead" effect for collaborative partnerships because maybe it takes real face-to-face interaction to form partnerships.

We argue this "step-ahead" effect is innocuous and is definitely not a form of secular divergent trend between the treated and controlled. Further, co-patents application in each year is a flow not a stock, so the "step-ahead" does not carry into the next period. We believe the slight divergence before the HSR connection can be attributed to the "step-ahead" effect and it is within statistical tolerance as suggested by the event study and placebo test. Therefore, we argue the common trend assumption still holds. But we think the reviewer's concern about the common trend is totally sensible, and thus we include an explanation in the paper on Page 15.

4). Other determinants of research collaboration that can be used to further reduce the omitted variable bias and the effects of heteroscedasticity in covariates include (but are not limited to:

-Research quality of participating firms and/or research institution -External research funding -Cognitive proximity between collaboration partners. -Firm characteristics of participating

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

For Peer Review Only

firms, including measures such as size, ownership structure, industry classification (ISIC), workforce skills, R&D intensity, and engagement in intra-mural vs external R&D activities, as well as access to R&D and innovation subsidies. -The nature of knowledge flows between a firm participating in a collaborative research and its partners; the subsequent innovation-related performance may therefore differ according to the interaction channel or the firm's R&D approaches (Maietta, 2015). -Institutional characteristics including familiarity with networking and knowledge transmission capability (Audretsch and Lehman, 2005; Landry et al., 2007; D'Este and Iammarino, 2010; Bonaccorsi et al., 2013). Individual characteristics of collaboration participants (research excellence, positions in the research units).

As an alternative approach to double difference, authors can use the non-parametric propensity score matching [PSM](Rosenbaum and Rubin, 1983) estimation to reduce the estimation bias as long as they can find enough data on most observable determinants of both the HSR connectivity between collaborating city pairs and the corresponding research collaboration efforts (or outcomes). PSM enables a better selection of a comparison group with similar characteristics. The requirement of common support ensures that the pairs being compared do not diverge in their characteristics related to the probability of being connected and their collaboration potential. One of the main advantage of PSM is that it can deal with all bias related to observable covariates and leaves out only the bias due to unobservable factors (Dehejia and Wahba, 1999; Ravallion, 2001; etc.).

Thanks for your comment. We appreciate the reviewer's suggestions on adding additional control variables to further reduce the omitted variable bias. In this study, the main dependent variable is the co-patents count between two cities and is aggregated from organizational-level co-patents data. The control variables suggested by the reviewers are at the organizational-level, which can not be directly matched and controlled in our city-level regression. Aggregating these variables to city-level means getting information of all the patent applying firms and research institutes for the whole country because we are using a complete collection of co-patents. That is difficult and unmanageable.

Thus, although many of the suggested control variables are sensible, some of the organizational-level control variables may not apply in our study. So instead of using organization-level variables, we include some additional city-level variables as substitutes.

"-Research quality of participating firms and/or research institution." This is an organizational-level variable. So instead of finding the research quality of all participating firms, we use city-level total single-applicant patent count divided by total industrial firms. This variable can be interpreted as patents per industrial firms, or the city-level average research quality of firms.

"-External research funding." This is also an organizational-level variable. Instead, we use a city-level variable scientific and technology fund provided by the city government for each industrial

For Peer Review Only

firm. It is constructed by total city-level S&T fund divided by number of industrial firms.

"-Cognitive proximity between collaboration partners. " "-Firm characteristics of participating firms, including measures such as size, ownership structure, industry classification (ISIC), workforce skills, R&D intensity and engagement in intra-mural vs external R&D activities, as well as access to R&D and innovation subsidies. " "-The nature of knowledge flows between a firm participating in a collaborative research and its partners; the subsequent innovation-related performance may therefore differ according to the interaction channel or the firm's R&D approaches (Maietta, 2015)." "-Individual characteristics of collaboration participants (research excellence, positions in the research units)." Again, we agree that those control variables are very relevant to firms' and institutes' decisions to engage in innovation collaboration, but due to data availability, we tried our best to find city-level control variables most relevant. In addition to the aforementioned control variables, we also include city-level R&D employment (related to the R&D intensity suggested by the reviewer) and city-level secondary and tertiary output share (related to industry classification suggested by the reviewer).

In summary, in addition to the control variables that were already included in the original version, such as city GDP, S&T expenditure, highway ridership, and mobile phone user, we have included new control variables such as patents per firm, S&T expenditure per firm, R&D employment per firm, total foreign-invested firms, secondary and tertiary output share. Also, the city-level fixed effect removes time-invariant idiosyncrasy. With new control variables, the main regression estimates remain consistent. In the main draft, we include the additional control variables for all regressions and replace the old statistics.

Reviewer 3 suggested Propensity Score Matching (PSM) to pair with the DID approach to ensure common support. A typical PSM-DID usually matches each treated observation with one or more controlled observations with similar characteristics. By doing so, the control group shrinks in size and share common support with the treatment group. In comparison, our DID model differs from the typical DID model in two ways.

First, there are multiple treatment periods instead of one. As cities were connected to the HSR network in different years, some observations were in the control group before they became parts of the treatment group. Thus, there is an unclear line between treatment and control groups as some observations can be both.

Second, there are more cities in the treatment group than in the control groups by the end period. That is, by 2018, there were 3,847 city-pairs that had been connected while 1,800 city-pairs had not. Using the traditional PSM method cannot match each treated observation with a controlled sample because one-to-one matching exhausts the control groups. One possible solution is to use a matching method with replacement, thus selecting some control observations repeatedly. However, the PSM method could nonetheless be problematic as cities in the control groups, which

For Peer Review Only

were not yet connected by 2018, are mostly small and medium cities because most major cities had been connected by 2018.

We agree with the reviewer that PSM can be a good method to achieve common support, but due to the two reasons mentioned above, the DID model in this study is not suitable for PSM. Moreover, we have already controlled for city and year fixed effects, which tease out city-level time-invariant factors and trend effect, and many important control variables as suggested by the reviewer. Therefore, missing variables should not be a concern for our DID model, but endogeneity from reverse causality can be a problem. As can be seen from our response to Reviewer 2, in the revised appendix, we tested endogeneity using an instrument variable approach to better ensure the robustness of our study. In the instrument regression result, the HSR effect on intercity innovation collaboration continues to hold.

Minor observation: P.12: "The main variable of interest is Connectijt, the one-year lagged dummy variable indicating whether City i and City j are both connected to HSR network in the year t." It is unclear how this variable is lagged: here, both the collaboration outcome and the connectivity seems to be measured at time t, so that the actual lag structure seems unclear.

Thanks for your pointing this out. It is a typo that should be fixed. We are using a one-year-lagged connection variable.

For Peer Review Only

References

Angrist, Joshua D and Jörn-Steffen Pischke, *Mostly harmless econometrics: An empiricist's companion*, Princeton university press, 2008.

Balland, Pierre-Alexandre, "Proximity and the evolution of collaboration networks: evidence from research and development projects within the global navigation satellite system (GNSS) industry," *Regional Studies*, 2012, *46* (6), 741–756.

_ , Ron Boschma, and Koen Frenken, "Proximity and Innovation: From Statics to Dynamics," *Regional Studies*, June 2015, *49* (6), 907–920.

Baum-Snow, Nathaniel, Loren Brandt, J Vernon Henderson, Matthew A Turner, and Qinghua Zhang, "Roads, railroads, and decentralization of Chinese cities," *Review of Economics and Statistics*, 2017, *99* (3), 435–448.

Bergé, Laurent R, Iris Wanzenböck, and Thomas Scherngell, "Centrality of regions in R&D networks: A new measurement approach using the concept of bridging paths," *Regional Studies*, 2017, *51* (8), 1165–1178.

Bin, Peng, Xiaolan Chen, Andrea Fracasso, and Chiara Tomasi, "Firm employment growth in China: The role of marketization and regional economic factors," *Growth and Change*, March 2020, *51* (1), 402–439.

Boschma, Ron, "Proximity and innovation: a critical assessment," *Regional studies*, 2005, *39* (1), 61–74.

Cao, Zhan, Ben Derudder, and Zhenwei Peng, "Interaction between different forms of proximity in inter-organizational scientific collaboration: The case of medical sciences research network in the Yangtze River Delta region," *Papers in Regional Science*, 2019, *98* (5), 1903–1924.

Chen, Gongmeng, Michael Firth, Daniel N Gao, and Oliver M Rui, "Ownership structure, corporate governance, and fraud: Evidence from China," *Journal of corporate finance*, 2006, *12* (3), 424–448.

Chen, Guanghua, Guoliang Yang, Feng He, and Kaihua Chen, "Exploring the effect of political borders on university-industry collaborative research performance: Evidence from China's Guangdong province," *Technovation*, 2019, *82*, 58–69.

Chen, Yang and Zheng Fang, "Industrial electricity consumption, human capital investment and economic growth in Chinese cities," *Economic Modelling*, 2018, *69*, 205–219.

Dong, Xiaofang, Siqi Zheng, and Matthew E Kahn, "The Role of Transportation Speed in Facilitating High Skilled Teamwork Across Cities," *Journal of Urban Economics*, 2019, p. 103212.

Etzkowitz, Henry and Loet Leydesdorff, "The dynamics of innovation: from National Systems and "Mode 2" to a Triple Helix of university–industry–government relations," *Research Policy*, February 2000, *29* (2), 109–123.

Fang, Chuanglin, Bo Pang, and Haimeng Liu, "Global city size hierarchy: Spatial patterns, regional features, and implications for China," *Habitat International*, 2017, *66*, 149–162.

Firth, Michael, Chen Lin, Ping Liu, and Sonia M L Wong, "Inside the black box: Bank credit allocation in China's private sector," *Journal of Banking & Finance*, 2009, p. 12.

Fischer, Manfred M, Thomas Scherngell, and Eva Jansenberger, "The geography of knowledge spillovers between high-technology firms in Europe: Evidence from a spatial interaction modeling perspective," *Geographical Analysis*, 2006, *38* (3), 288–309.

Greene, William H., *Econometric analysis*, 7th ed ed., Boston: Prentice Hall, 2012. OCLC:

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

For Peer Review Only

ocn692292382.

Haixiao, Pan and Gao Ya, "Development of High-Speed Rail in the People's Republic of China," *Social Science Electronic Publishing*, 2019.

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

Jaffe, Adam B, Manuel Trajtenberg, and Rebecca Henderson, "Geographic localization of knowledge spillovers as evidenced by patent citations," *the Quarterly journal of Economics*, 1993, *108* (3), 577–598.

Lata, Rafael, Thomas Scherngell, and Thomas Brenner, "Integration processes in European research and development: A comparative spatial interaction approach using project based research and development networks, co-patent networks and co-publication networks," *Geographical Analysis*, 2015, *47* (4), 349–375.

Li, Hongbin, Lingsheng Meng, and Junsen Zhang, "Why Do Entrepreneurs Enter Politics? Evidence from China," *Economic Inquiry*, July 2006, *44* (3), 559–578.

Maietta, Ornella Wanda, "Determinants of university–firm R&D collaboration and its impact on innovation: A perspective from a low-tech industry," *Research Policy*, September 2015, *44* (7), 1341–1359.

Mao, Qiliang and Xianzhuang Mao, "Cultural barriers, institutional distance, and spatial spillovers: Evidence from regional industrial evolution in China," *Growth and Change*, July 2021, p. grow.12527.

Marek, Philipp, Mirko Titze, Clemens Fuhrmeister, and Ulrich Blum, "R&D collaborations and the role of proximity," *Regional Studies*, December 2017, *51* (12), 1761–1773.

Maurseth, Per Botolf and Bart Verspagen, "Knowledge spillovers in Europe: a patent citations analysis," *Scandinavian Journal of Economics*, 2002, *104* (4), 531–545.

Neter, John, Michael H Kutner, Christopher J Nachtsheim, William Wasserman et al., *Applied linear statistical models*, Irwin Chicago, 1996.

Ponds, Roderik, Frank Van Oort, and Koen Frenken, "The geographical and institutional proximity of research collaboration," *Papers in regional science*, 2007, *86* (3), 423–443. Publisher: Wiley Online Library.

Ravallion, Martin, "The mystery of the vanishing benefits: An introduction to impact evaluation," *the world bank economic review*, 2001, *15* (1), 115–140.

Scherngell, Thomas and Yuanjia Hu, "Collaborative Knowledge Production in China: Regional Evidence from a Gravity Model Approach," *Regional Studies*, 2011, *45* (6), 755–772.

Sun, Yutao and Cong Cao, "Intra- and inter-regional research collaboration across organizational boundaries: Evolving patterns in China," *Technological Forecasting and Social change*, 2015, p. 17.

Torre, Andre and Alain Rallet, "Proximity and Localization," *Regional Studies*, February 2005, *39* (1), 47–59.

Wang, Xiaolu, Gang Fan, and Jingwen Yu, "Marketization index of China's provinces: NERI report 2016," *Social Sciences Academic Press: Beijing, China*, 2017.

For Peer Review Only

Intercity Innovation Collaboration and the Role of High-speed Rail Connections: Evidence from Chinese Co-patent Data

For Peer Review Only

Abstract

This study explores the extent to which changes in transport infrastructure counterbalance pre-existing geographic friction and foster innovation collaboration, using the Chinese HSR construction as a quasi-natural experiment. Using a comprehensive dataset of city-pair co-patents from 2005 to 2018, we show that HSR connection significantly increases inter-city co-patents, patent quality, and collaborative partnerships, and such effects are strongest for city-pairs within 250 km and decrease for longer distances. Moreover, the HSR effect is stronger for cities in similar institutional setting, indicating a negative moderating effect of institutional distance. Various robustness methods are used to confirm the validity of our findings.

Keywords: Innovation collaboration, Co-patent, High-speed Rail, Geographical proximity, Institutional proximity

1 Introduction

Inter-city innovation collaborations need to overcome geographic friction. Early research (e.g. Maurseth and Verspagen, 2002; Fischer et al., 2006) that followed Jaffe et al.'s (1993) seminal work found a substantial influence of geographical proximity on innovation collaboration. However, later research that embraced Boschma's (2005) fivefold classification of proximity as an analytical framework has produced the more balanced findings. Firstly, geographical proximity is found to be less influential than previously assumed once non-geographical forms of proximity are considered in innovation collaboration (Torre and Rallet, 2005; Boschma, 2005; Balland et al., 2015). Secondly, geographical and non-geographical forms of proximity are often found to be positively correlated (Balland et al., 2015). Nonetheless, geographical proximity is still found to positively influence the formation of innovation collaboration when other forms of proximity are included in studies (Hong and Su, 2013; Marek et al., 2017; Cao et al., 2019).

If geographical distance remains a noticeable barrier to inter-city innovation collaboration, to what extent do changes in infrastructure counterbalance pre-existing geographic friction and foster innovation collaboration? While the limited studies have shown that reductions in communication costs and travel costs as a result of technological advancement mitigate geographic friction (Agrawal and Goldfarb, 2008; Catalini et al., 2020), these studies also point to the differential impact on innovators across urban systems. For example, Agrawal and Goldfarb (2008) examined the adoption of the Internet on university research collaboration in engineering and found reductions in communication costs increased research collaboration between top-tier and middle-tier institutions from the same region. Catalini et al. (2020) looked at the impact of the introduction of new routes by a low-cost airline on scientist collaboration. They found that reductions in travel costs mitigated geographic friction to collaboration and increased the number of collaborations between 0.3 and 1.1 times. Still, we do not know much about the collaboration-enhancing effect of changes in infrastructure and the cost-induced complementary effect of geographical and institutional proximities.

More recently, the construction of high-speed rail (HSR) in many countries has again raised the question of how HSR can help overcome geographical distance and facilitate inter-city innovation collaboration. Currently, the world has 52,418km of high-speed network in commercial operation and 11,693km of high-speed lines under construction, of which China made up no less than 50% (Guigon, 2020). HSR is one of the most advanced modes of ground transportation that could operate at a speed of over 200 km per hour. As a key national development strategy in China, the construction of a nationwide HSR network aims to improve connectivity between regions and promote a more balanced and equitable regional development (Chen and Haynes, 2017). The sheer scale of HSR connectivity in China, as can be seen in Figure 1, and the advantages of HSR over other alternatives—such as high speed, convenience, comfortable experience, proximity to city centers, punctuality, and safety—have tremendously transformed the way people travel and

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

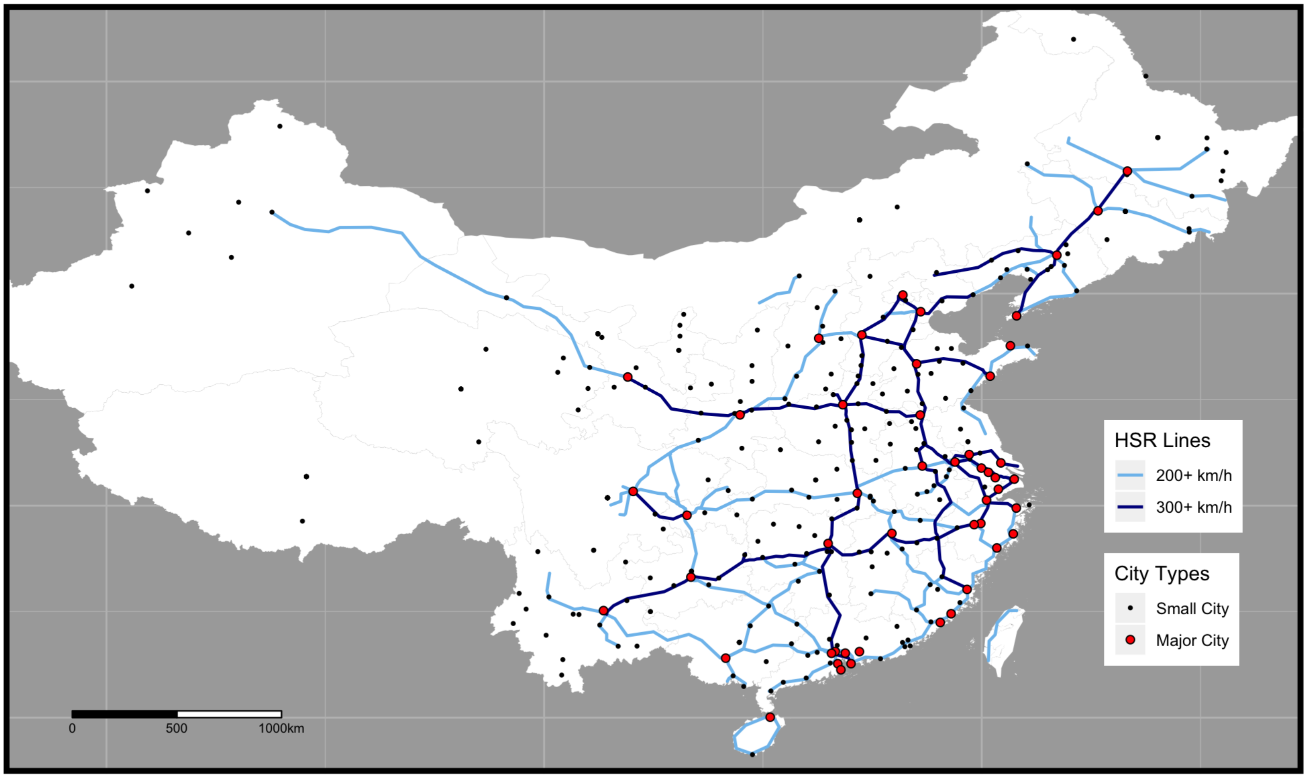


Figure 1: A Map of Chinese HSR Network at the End of 2018

become one of the most popular forms of intercity passenger transportation.

So far, the limited research on HSR and innovation has produced some interesting findings. For example, Inoue et al. (2017) used the case of the opening of the Shinkansen in Japan to estimate the impact of HSR on innovative activities along the line. They found that HSR significantly increased patent submissions and patent citations by establishments along the line. Gao and Zheng (2020) used innovation surveys to assess the impact of HSR on innovation in manufacturing firms in the Yangtze River Delta and Pearl River Delta, China's two most developed regions. The results show that HSR connection promotes firm innovation in peripheral areas. Dong et al. (2019) specifically investigated the impact of HSR on inter-city university research collaboration, using a dataset of research paper publication and citations. They found that when cities are connected by HSR, co-author productivity from existing collaborations rises, new co-author pairs emerge and more highly productive scientists migrate to the HSR cities. Building on studies with a focus on infrastructure and innovation, we aim to unpack the differential impact of HSR by addressing our first research question: To what extent does HSR affect inter-organizational innovation collaboration across HSR-connected cities? First, we use dyadic city-pair co-patent panel data to capture more accurately the differential effect of HSR on intercity co-patent collaboration through two mechanisms, i.e., HSR-induced intensity of face-to-face interactions, and HSR-induced partner matching in larger labor markets. Second, we disentangle the HSR effect across urban systems and on different types of innovators in the manifestation of inter-firm collaboration (II) and university and research institute collaboration (URI).

Extant research on innovation and proximity has explored the impact of institutional proximity on innovation collaboration. As Balland et al. (2015) noted, however, researchers have used two different definitions of institutional proximity, i.e., the degree to which organizations share similar institutional settings at macro level (Boschma, 2005), and values and norms in the same subsystem within academia, industry, or government, following the triple helix model (Etzkowitz and Leydesdorff, 2000; Ponds et al., 2007). As compared to studies that examined the impact of organization-level institutional proximity using the second definition (e.g. Ponds et al., 2007; Hansen, 2015; Cao et al., 2019), the impact of region-level institutional proximity adopting the first definition is under-researched. So far, only two studies can be found. Hong and Su (2013) analyzed the effect of institutional proximity on non-local university-industry collaborations in China. The results show that institutional proximity caused by subordination to the same administrative unit significantly enhances the probability of collaboration, and those effects are more significant when the distance increases, suggesting the substitution effect. Marek et al. (2017) explored the impact of proximity measures on knowledge exchange measured by granted research and development (R&D) collaboration projects in German NUTS-3 regions. They found a 'U'-shaped impact of institutional distance on inter-regional collaboration with a negative impact, which shrinks after passing a distinct threshold level. We complement these works to assess the synergetic effect of HSR and institutional distance from a decentralization perspective. China has an economic system characterized by both high centralization and strong decentralization (Bai et al., 2004). Decentralization comes with local economic agendas and local protection (Bai et al., 2004). This decentralized system has a huge impact on how organizations collaborate. Yet, our understanding of how HSR affects inter-city innovation collaboration in a decentralized institutional system is limited. Our research intends to fill this void by exploring our second research question: to what extent does institutional proximity moderate the HSR-mitigated relationship between geographical proximity and inter-city innovation collaboration?

Our study makes three contributions to the proximity and innovation literature. First, we enrich the literature on geographical proximity and innovation collaboration by unraveling the HSR-mitigated differential effect of geographic friction on the quantity and quality of inter-city innovation collaborations. Second, we draw on a regional decentralization perspective to explore how institutional proximity moderates the HSR effect. Thus, we enrich the literature by providing a more nuanced understanding of how different dimensions of proximity interact to affect inter-city innovation collaboration. Third, we again follow the decentralization perspective to explore whether the HSR effect is more constrained in geographical distance for II collaboration and more constrained in institutional distance for URI collaboration. Our research, therefore, sheds new

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

light on how different types of innovation actors with varying inherent incentives and behaviors may respond differently to the improved transportation infrastructure and manifest themselves differently in intercity innovation collaboration.

2 Theoretical Framework and Hypothesis Development

For innovation collaboration, face-to-face communication is of importance throughout all stages of the process. At the initial stage, it is essential for firms to match up with the right types of partners—such as vertical (suppliers), horizontal (competitors), or institutional (universities and research institutes) partners—that complement themselves with the necessary knowledge and resources to achieve the goals pursued. Once a partnership or alliance is formed, it is necessary for team members to become familiar with each other, to develop an enhanced understanding of the problem-solving procedure, to cultivate personal trust, and eventually to build effective research routines so as to improve efficiency and prospect for project success (Bercovitz and Feldman, 2011). Therefore, close face-to-face contact is essential throughout the whole process of innovation collaboration.

HSR, as an advanced transportation infrastructure, provides a faster, safer, more comfortable, and arguably the most punctual transportation service than other alternatives, such as regular train, automobile, and air flights (Sun et al., 2017). It fills a blank of traveling at a distance too far for cars and too close for flights. Hence, HSR facilitates more cost-effective inter-city travel for face-to-face contact and collaborative innovation. Overall, HSR affects intercity innovation collaboration through two mechanisms. First, HSR helps increase the intensity of interaction between collaborative partners between connected cities.

HSR connections significantly shrink the geographical distance between cities because of high travel speed at relatively lower costs. This cost-effective transport mode allows team members in inter-organizational collaborative projects to interact face to face more in order to build rapport, share tacit knowledge, and resolve differences. The increasing intensity of interaction has two implications. First, it enhances the efficiency of innovation collaboration that leads to a better performance of co-patenting in quantitative terms. Such an effect should be stronger for city-pairs that within HSR travel time. Studies have shown that within 600km, the HSR travel experience dominates the alternatives, including that of air travel (Lawrence et al., 2019). Therefore, the HSR effect on intercity innovation collaboration should be more salient for city-pairs that are geographically close and within the HSR range. Second, more face-to-face interactions between innovation partners across HSR-connected cities also improve collaborators' cognitive proximity due to greater knowledge sharing, hence elevating innovation outcomes, such as patent quality. Dong et al.'s (2019) research on academic co-publication found the positive effect of HSR on both quantity and quality of co-publication. Therefore, we propose the following.

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

Hypothesis 1a *HSR increases the quantity of collaborative innovation between connected city-pairs.*

Hypothesis 1b *HSR connection improves quality of collaborative innovation between connected city-pairs.*

Second, HSR increases opportunities for partner matching in larger markets. Firstly, because HSR increases travel speed across cities, it thus creates a larger market for organizations to match partners for innovation projects. The increased cross-city travel speed at lower costs facilitates the better matching of researchers with complementary skills in a larger scientist labor market, leading to the formation of more innovation collaborative partnerships between the connected city-pairs. Secondly, by establishing connections between core markets (megacities) and outside markets (smaller cities), transport improvements expand the geographical reach of knowledge spillover, thereby enabling organizations in outside markets to do new things or to accomplish old tasks in new ways, and energize innovation in other sectors. Accordingly, HSR connections again lead to the formation of more innovation collaborative partnerships between the connected city-pairs. Hence, we propose the following:

Hypothesis 1c *HSR increases the number of innovation collaborative partnerships between connected city-pairs.*

In addition to geographical distance, intercity innovation collaboration can be constrained by the intercity discrepancy in formal and informal institutions (North et al., 1990), or institutional distance. A distinct feature of the economic system in Chins is administrative decentralization (Perkins, 1988). The devolution of decision-making power from the center to local governments allows locally available information to be used more effectively and local preferences to have greater influence over local spending decisions (Chen, 1998). Inevitably, the system leads to the diversity of regulative institutions in terms of rules, laws, and sanctions through the coercive mechanism (Scott, 2013). The unintended consequences of such a decentralized system are local governments' zeal for GDP growth and local protectionism (Bai et al., 2004). Local governments prefer to support local business development and local inter-organizational collaboration as government officers are more likely to get promotions if local economic growth can benefit from significant innovations within their territories (Hong and Su, 2013). Hence, institutional diversity between regions gives rise to unpredictable and unreliable conditions under which effective inter-organizational innovation collaborations are more difficult to take place. Regional institutional discrepancies and protectionism impede cross-region innovation collaboration (Ding and Li, 2015).

Despite lower travel costs incurred by HSR connections, institutional differences persist among provinces. Therefore, the HSR effect is moderated by institutional distance, i.e., HSR connections

For Peer Review Only

increase more innovation collaboration between city-pairs that are within the same province than those across provinces. For the aforementioned reasons, we propose the following hypothesis:

Hypothesis 2 *Institutional distance moderates the positive effect of HSR connection on innovation collaboration between connected city-pairs.*

Patents as an embodiment of commericializable technologies are created and applied by various innovative actors. Firms, universities, and research institutions are three key innovative actors in the national innovation system (NIS). It is important to distinguish two types of inter-organizational collaborations, i.e., collaborations involving universities and research institutes (URI)[1] and intra-industrial collaborations (II) because different knowledge types are affected in different dimensions of proximity (Davids and Frenken, 2018). Since most universities and research institutes are public-funded institutions in China, intercity URI collaborations are driven by the government's social and economic policies and aim to produce public goods. In contrast, intercity II collaborations are motivated by business interest and aim to deliver private goods. Comparatively, URI collaborations led by universities and research institutes are influenced by government agendas in the Chinese context, and therefore are less sensitive to economic costs but are more likely to succumb to the stick and carrot approach used by local governments. For such reasoning, we propose the following hypotheses:

Hypothesis 3a *The HSR effect is stronger within close distance for II collaborations than URI collaborations.*

Hypothesis 3b *HSR effect is stronger within the same province for URI collaborations than II collaborations.*

3 Data

3.1 Data and Statistics

Co-patent data from the China National Intellectual Property Administration (CNIPA) is used in this study. We collected data of all patents with two or three applicants over the period of 2005-2018 from the database *incopat.com*.

All co-patent data include two or three applicants who could be individuals, firms, universities, or research institutes. We construct intercity co-patents by using the information of applicant addresses. For a patent with applicants from City A and B, we construct the city-pair as A-B,

[1] URI collaborations include university-university (UU), university-research institutes (UR), university-industry (UI), and research institute-industry (RI). Any co-patents involving universities or research institutes are categorized as URI collaborations.

For Peer Review Only

while for three-applicant from City A, B, and C, we then create three city-pairs, A-B, A-C, and B-C but with 1/3 of weight each. There are 293 prefecture cities and 4 municipalities in China in 2018. We only consider the cities that had intercity co-patents and exclude those without, which leaves us a total of 285 prefecture-level and above cities. The original dataset contains 1 million co-patents, and after data cleaning, it is down to 708,002, of which, 386,735 are intercity co-patents. We exclude intracity collaborations in our research sample.

We use three dependent variables. The first is $CoPat_{ijt}$, the count of co-patents between City i and j during the year t as the measure of the quantity of collaborative innovation. The second is the value-weighted patent $CoPatW_{ijt}$ as a measure of the quality of collaborative innovation. The third dependent variable is $CoPatP_{ijt}$ (collaborative partners) as a measure of the quantity of innovation collaborative partnership. Once two organizations cooperate for at least one co-patent in one year, they are defined as innovation collaborative partners.

A city is connected to the HSR network once at least one station is opened. The opening dates and routes of HSR are collected from the official website *12306.cn*, maintained by the National Railway Administration of China. The dummy variable $connect_{ijt}$ is coded one if both the Cities i and j are HSR connected in year t and zero otherwise.

We construct a city-pair panel dataset including all cities with at least one co-patent over 14 years from 2005 to 2018. We exclude the city-pairs that never had any collaborations, and only keep the city-pairs that had at least one collaboration over 14 years. There are a total of 79,058 observations over 14 years on 5,647 unique city-pairs. The main independent variables of interest in addition to $Connect_{ijt}$ are $Distance_{ij}$ and $SameProv_{ij}$, which indicate the distance between Cities i and j and whether the two cities belong to the same province. Geographical distances are measured in straight-line (or Euclidean) distance between cities using geographical information. The literature has used both straight-line distance and travel time to measure geographical distance, but they generate very similar results (Marek et al., 2017). Most of gravity-based models use straight-line distance for its lower cost. Following Hong and Su (2013), we use the provincial-border definition of institutional distance. It implies that cities belonging to the same province are considered institutionally approximate and incur no institutional friction because they are subject to the same regulative institution. For all the specifications, we control city and year fixed effects, which tease out time-invariant city-level characteristics and time trending effects. Besides, we control other time-variant confounding variables that possibly affect the intercity co-patents, including city-level GDP, total single-applicant patents, science and technology government expenditure, etc. Table 1 summarizes the definition and sources of the dependent, independent, and control variables.

Table 2 reports the descriptive statistics of the main dependent and independent variables. As can be seen from the table, the distribution of $CoPat$ is quite skewed with a mean of 4.13 and a standard deviation of 37.02, and a large number of those observations are zeros. In light of con-

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk
For Peer Review Only

Table 1: Variable Definition

Variable	Definition
Outcome Variables:	
$CoPat_{ijt}$:	Total co-patent count between City i and City j
$CoPatW_{ijt}$:	Co-patents weighted by patent values. Patent value is calculated by *incopat.com* using big data technique and including information such as patent citation, assignment, licensing, legal status, and other determinant variables.
$CoPatP_{ijt}$:	Co-patent partnerships between City i and j in year t. Calculated using unique collaborative pairs from the variable $CoPat_{ij}$.
$CoPat(URI)_{ijt}$:	Co-patents involving universities and research institutes between City i and j in year t. $CoPatP(URI)_{ijt}$ is URI partnerships.
$CoPat(II)_{ijt}$:	Intra-firm co-patents between different firms between City i and j in year t. $CoPat(II)_{ijt}$ is II partnerships.
Independent Variables:	
$Connect_{ijt}$:	A time-variant dummy variable indicating whether City i and j are connected to HSR in year t with one year lag. The data is collected from *www.12306.cn*, which maintained by the National Railway Administration of the PRC.
$Distance_{ij}$:	A time-invariant variable measures the straight-line (Euclidean) distance between City i and j in kilometers.
$Dist.S_{(0\sim 250km)}$:	A time-invariant dummy variable coded one when the city-pair is with 250 km distance. $Dist.M_{(250\sim 600km)}$ and $Dist.L_{(600\sim 1000km)}$ are respectively for median and long range dummy variables.
$SamePro_{ij}$:	A time-invariant dummy variable indicating whether City i and j located in the same province.
Control Variables:	
$SinglePat_{it}$:	Total single-applicant patents for City i in year t.
GDP_{it}:	Total gross production in millions.
$SciExp_{it}$:	Government expenditure in science and technology in millions.
$HwayRidership_{it}$:	Total highway ridership in thousands.
$MobileUsers_{it}$:	Total mobile phone users in thousands.
$PatentPerFirm_{it}$:	Total patents per industrial firm.
$S\&TPerFirm_{it}$:	Expenditure in science and technology per industrial firm.
$R\&DPerFirm_{it}$:	R&D employment per industrial firm.
$FIEs_{it}$:	Total foreign invested firms.
$SecondaryShare_{it}$:	Secondary industry output share.
$TertiaryShare_{it}$:	Tertiary industry output share.

siderable over-dispersion and a larger number of zero observations, negative binomial regressions are used throughout the analyses. Table 2 also reports other outcome variables including weighted co-patents, partnerships, and also URI and II co-patents and partnerships.

The correlation analysis in Table 2 suggests the key independent variables such as *Connect*, *SameProv*, and *Distance* all have relatively low and moderate correlation coefficients with other variables. Moreover, to test multicollinearity, we inspected the variance inflation factors (VIFs) of the variables using linear regression (the convention is to use linear regression when the main

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk
For Peer Review Only

Table 2: Statistics Summary and Correlation Analysis for the Main Dependent and Independent Variables

	Variables	Observations	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	$CoPat$	79058.00	4.13	37.02	1.00													
2	$CoPatW$	79058.00	4.18	37.95	0.99	1.00												
3	$CoPat(Top)$	79058.00	2.31	21.60	0.96	0.98	1.00											
4	$CoPatP$	79058.00	1.34	7.40	0.80	0.79	0.75	1.00										
5	$CoPat(II)$	79058.00	3.07	31.99	0.98	0.97	0.94	0.73	1.00									
6	$CoPat(URI)$	79058.00	1.06	8.72	0.66	0.65	0.62	0.75	0.49	1.00								
7	$CoPatP(II)$	79058.00	0.69	4.18	0.81	0.80	0.75	0.96	0.76	0.64	1.00							
8	$CoPatP(URI)$	79058.00	0.65	3.56	0.72	0.71	0.67	0.95	0.61	0.80	0.83	1.00						
9	$Connect.lag1$	79058.00	0.25	0.43	0.12	0.11	0.11	0.17	0.10	0.12	0.16	0.17	1.00					
10	$Distance$	79058.00	939.12	635.20	-0.03	-0.03	-0.03	-0.05	-0.03	-0.04	-0.04	-0.05	-0.01	1.00				
11	$SameProv$	79058.00	0.14	0.35	0.01	0.01	0.01	0.03	0.00	0.05	0.01	0.06	-0.04	-0.46	1.00			
12	$Dist.S_{(0\sim250km)}$	79058.00	0.10	0.30	0.04	0.04	0.03	0.08	0.02	0.07	0.05	0.10	-0.01	-0.44	0.66	1.00		
13	$Dist.M_{(250\sim600km)}$	79058.00	0.25	0.43	-0.00	-0.00	-0.01	-0.01	0.00	-0.01	-0.01	-0.01	-0.00	-0.49	0.11	-0.20	1.00	
14	$Dist.L_{(600\sim1000km)}$	79058.00	0.24	0.43	-0.01	-0.01	-0.01	-0.02	-0.01	-0.02	-0.01	-0.02	0.03	-0.13	-0.22	-0.19	-0.32	1.00

For Peer Review Only

regression model is non-linear). The VIFs value for *Connect*, *SamePro*, and *Distance* are respectively 5.1, 1.66, and 1.68 , which are below the acceptable level of 10 (Neter et al., 1996). Hence, multicollinearity is not a concern in our case.

4 Empirical Strategy and Results

We apply a difference-in-differences (DID) approach to test the effects of HSR on intercity innovation collaboration. Because intercity innovation collaborations are dyadic in nature, we apply a variant of gravity model—an empirical method originally used in international trade literature, and then increasingly adopted in invention collaboration and knowledge flow literature (Picci, 2010; Cappelli and Montobbio, 2016). Our regional gravity model considers innovation collaboration in three measures as a function of the distance between cities and time-variant economic variables that potentially affect inter-city innovation collaboration. We formulate the following baseline regression model:

$$Y_{ijt} = \alpha_0 + \alpha_1 Connect_{ijt} + \alpha_2 Dist_{ij} + \alpha_3 SameProv_{ij} + X\beta + \delta_i + \delta_j + \tau_t + \epsilon_{ijt} \qquad (1)$$

The main variable of interest is $Connect_{ijt}$, the one-year lagged dummy variable indicating whether City i and City j are both connected to the HSR network in the year t-1[2]. $Dist_{ij}$ is a continuous variable of the straight-line distance between City i and City j in kilometers. $SameProv_{ij}$, a dummy variable, indicates whether two cities are located in the same province, which is interpreted as institutional proximity. X stands for the time-variant control variables for City i and j. δ_i and δ_j indicate the fixed-effects of City i and City j respectively. τ_t is the year dummy and ϵ_{ijt} is the error term.

The data and method we use have two advantages. First, we use a full set of Chinese co-patent data across all industries, so our data are representative of all ranges of technologies. Second, dyadic city-pair observations combined with the gravity model could better identify the effects of geographical and institutional distance. In all estimations, we apply the negative binomial gravity model framework.

[2] We use a binary dummy variable indicating whether a city is connected to the HSR network for two reasons. First, easier interpretation—using binary variables we can interpret the results as treatment effect. A continuous variable such as volume or number of trains can be difficult to interpret. Second, the HSR effect is unlikely to be linear in relation to the volume or numbers of trains.

For Peer Review Only

4.1 The Baseline Result

Table 3 presents the baseline results from three model specifications. Model (1) excludes city-level variables and fixed effects. From pooled regression in Model (1), HSR connections show a positive and significant effect, meaning connected city-pairs tend to have a larger number of co-patents than those unconnected.

Table 3: The Baseline Regression of Negative Binomial Regressions

	Dependent Variable: $CoPatent$		
	(1)	(2)	(3)
$Connect$	1.972***	0.009	0.042
	(0.059)	(0.056)	(0.071)
$Distance$	−0.001***	−0.001***	−0.001***
	(0.0001)	(0.0001)	(0.00004)
$SameProv$	−0.121	1.312***	1.431***
	(0.087)	(0.057)	(0.050)
$Dist.S_{(0\sim250km)}$		0.344***	
		(0.097)	
$Dist.M_{(250\sim600km)}$		−0.004	
		(0.078)	
$Dist.L_{(600\sim1000km)}$		−0.021	
		(0.060)	
$Connect \times Dist.S_{(0\sim250km)}$		0.261***	
		(0.075)	
$Connect \times Dist.M_{(250\sim600km)}$		0.131*	
		(0.073)	
$Connect \times Dist.L_{(600\sim1000km)}$		−0.051	
		(0.069)	
$Connect \times Distance$			−0.00002
			(0.00005)
$Connect \times SameProv$			0.301***
			(0.077)
$CityPair\ Controls$	No	Yes	Yes
$City\&Year\ FE$	No	Yes	Yes
Observations	79,058	78,834	78,834
Akaike Inf. Crit.	201,818.700	170,575.300	170,666.300

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors are clustered at the city level.

In Model (2), we additionally control for the interaction term of distance ranges with HSR connection: $Connect \times (Dist.S + Dist.M + Dist.L)$. $Dist.S$ is coded as one if the city-pair is within 250km distance range, about 1.5 hours travel time by HSR. Similarly, $Dist.M$ and $Dist.L$ indicate city-pairs of distance ranging from 250 to 600 km and from 600 to 1000 km. The interaction coefficients of *connect* with the range dummy variables suggest the extent to which HSR connection

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

For Peer Review Only

increases the number of co-patents between city-pairs within those ranges. The coefficient of $Connect \times Dist.S_{(0\sim250km)}$ is significant and positive at 0.261, meaning that HSR is effective in increasing innovation collaborations between connected city-pairs within 250km by 26.1%. From 250 to 600 km, though insignificant, HSR connection accounts for a 13.1% increase in co-patents, while from 600 to 1000 km, the effect is negative. Therefore, the results of Model (2) support Hypothesis 1a, indicating that HSR connection increases intercity innovation collaborations. The HSR effect is most significant within 250 km but diminishes by longer distances.

Model (3) additionally controls for the interaction term: $Connect \times (Distance + SameProv)$, which is to examine whether being in the same province, conditional on geographical distance, moderates the effect of HSR connection. The interaction shows a positive and significant effect at 0.301, suggesting that HSR connection increases by 30.1% for cities that are within the same province after controlling for geographical distance. That is, institutional proximity complements HSR connection in facilitating intercity co-patents. In other words, the HSR effect is moderated by institutional distance. Hence, it supports Hypothesis 2.

4.2 Innovation Quality and Partnerships

To test the effect of HSR connection on quality of co-patent value and the number of collaborative partnerships, we use the same regression specifications as in Model (2) and (3) from Table 3, but with different dependent variables.

In Table 4, Columns (1) and (3) report the interaction effect within different distance ranges, and Columns (2) and (4) report the interaction with institutional proximity. For regressions on value-weighted co-patents, Column (1) suggests that HSR connect increases value-weighted co-patents by 28.5% within 250km, higher than 26.1% in the simple patent count in the baseline estimation. The difference suggests that the increased innovation collaborations as a result of HSR connection also tend to produce higher innovation value, hence confirming Hypothesis 1b. Column (2) shows that HSR connection increases valued-weight co-patents by 30.4%, which is similar to 30.1% in the baseline estimate, suggesting that co-patent quality increases for collaboration between cities of geographical proximity but not institutional proximity.

Regressions on co-patent partnerships in Columns (3) and (4) reveal slightly differential HSR effects on the dimension of geographical and institutional proximity. On one hand, there is a weak significant HSR effect on forming collaborative partners for cities of geographical proximity, indicating that most of the increased co-patents are from the deepening of existing collaborative partnerships. On the other, HSR connection increases collaborative partners for cities of institutional proximity (being in the same province). Hence, there are both deepening and widening effects on collaboration between cities of the same province. A further analysis, which breaks down the types of innovators, reveals a more nuanced pattern of how HSR affects intercity collaborative partnerships where Hypothesis 1c can be partially supported.

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk
For Peer Review Only

Table 4: Regressions on Value Weighted Co-patents and Partnerships

	Dependent Variable:			
	Value-weighted		Partnerships	
	(1)	(2)	(3)	(4)
$Connect$	0.009	0.063	−0.007	−0.102**
	(0.083)	(0.097)	(0.048)	(0.043)
$Distance$	−0.001***	−0.001***	−0.001***	−0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$SameProv$	1.415***	1.543***	1.264***	1.487***
	(0.134)	(0.122)	(0.104)	(0.087)
$Connect \times Dist.S_{(0\sim250km)}$	0.285***		0.102*	
	(0.105)		(0.061)	
$Connect \times Dist.M_{(250\sim600km)}$	0.164		−0.049	
	(0.125)		(0.056)	
$Connect \times Dist.L_{(600\sim1000km)}$	−0.058		−0.031	
	(0.146)		(0.064)	
$Connect \times Distance$		−0.00003		0.0001
		(0.0001)		(0.00005)
$Connect \times SameProv$		0.304***		0.223***
		(0.114)		(0.064)
$Control\ Variables$	Yes	Yes	Yes	Yes
$City, Year\ FE$	Yes	Yes	Yes	Yes
Observations	78,834	78,834	78,834	78,834
Akaike Inf. Crit.	156,252.300	156,339.900	138,473.600	138,896.600

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the city level. The odd-number columns follow the Model (3), and the even-number columns follows Model (4) in the baseline results of Table 3. Some non-essential variables are omitted.

For Peer Review Only

4.3 Comparison between URI and II Collaborations

Table 5 presents the regression results that explore the difference between URI and II co-patents. Columns (1) and (5) are regressions on co-patent counts, which shows that HSR connection increases II co-patents by 27.6% and URI co-patents by 18.9%, suggesting the greater effect of HSR connection on II than URI collaboration within 250 km. Between 250 and 600km, the coefficient is also greater for II than URI collaborations, but both effects are insignificant. Columns (3) and (7) are regressions on collaborative partnerships, which show that HSR connection has a positive and significant effect on the formation of innovation partnerships for II but not for URI collaborations. Together, the results confirm our hypothesis 3a, indicating that HSR connection has a greater effect on II than URI collaborations so far as geographical dimension is concerned.

For Columns (2), (4), (6), and (8), the regressions explore the effect of institutional dimension on HSR connection and both II and URI collaborations. The coefficients on $Connect \times SameProv$ suggest that HSR connection increases within provincial innovation collaborations more for URI and II types. For II co-patents, the HSR effect on co-patent count is weakly significant at 0.198

Table 5: Regression Comparison between URI and II Co-patents

	Dependent Variable: Co-patent Count and Partnerships							
	II-CoPatents		II-Partnerships		URI-CoPatents		URI-Partnerships	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Connect	−0.043	0.039	−0.029	−0.067	0.042	−0.157*	0.010	−0.257***
	(0.094)	(0.102)	(0.074)	(0.073)	(0.047)	(0.083)	(0.047)	(0.063)
Distance	−0.001***	−0.001***	−0.001***	−0.001***	−0.0005***	−0.001***	−0.0005***	−0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
SameProv	1.201***	1.272***	0.993***	1.156***	1.640***	1.870***	1.629***	1.863***
	(0.138)	(0.101)	(0.115)	(0.085)	(0.096)	(0.110)	(0.096)	(0.100)
$Connect \times Dist.S_{(0\sim250km)}$	0.276**		0.165*		0.189**		−0.013	
	(0.122)		(0.094)		(0.086)		(0.086)	
$Connect \times Dist.M_{(250\sim600km)}$	0.149		−0.002		−0.053		−0.134**	
	(0.135)		(0.076)		(0.067)		(0.067)	
$Connect \times Dist.L_{(600\sim1000km)}$	−0.013		0.033		−0.165***		−0.136**	
	(0.150)		(0.090)		(0.053)		(0.053)	
$Connect \times Distance$		−0.00004		0.00004		0.0001*		0.0002***
		(0.0001)		(0.0001)		(0.0001)		(0.0001)
$Connect \times SameProv$		0.198		0.209***		0.435***		0.311***
		(0.147)		(0.074)		(0.134)		(0.083)
City Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	79,058	79,058	79,058	79,058	79,058	79,058	79,058	79,058
Akaike Inf. Crit.	119,984.300	120,002.100	94,778.950	94,926.000	105,502.600	105,744.000	93,477.190	93,894.030

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the city level. Some non-essential variables are omitted.

For Peer Review Only

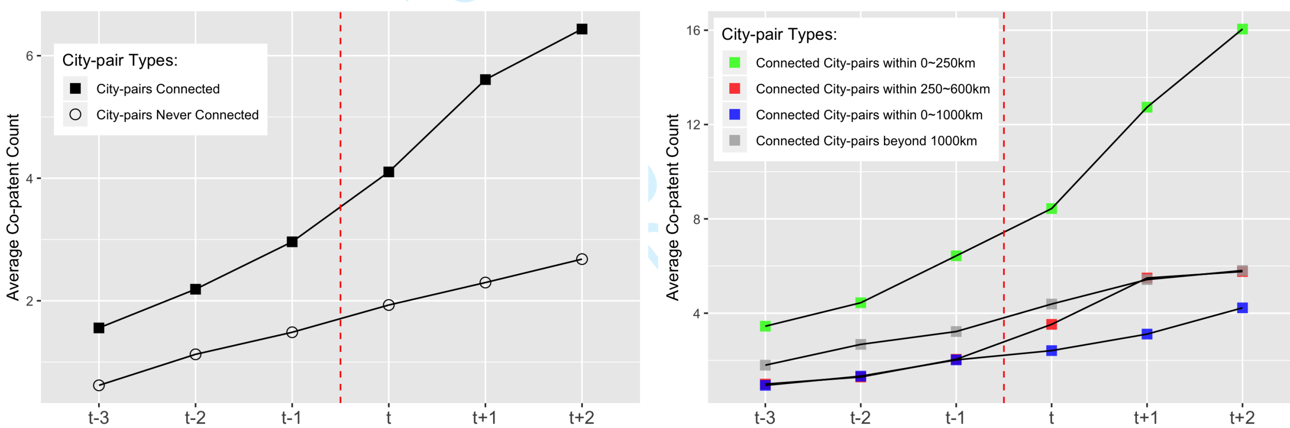
and the effect on the formation of partnerships is 0.209. Both numbers are noticeably smaller than the coefficient for URI at 0.435 and 0.311. Thus comparison of HSR effect on II and URI collaborations again confirms Hypothesis 3b.

5 Robustness Check

5.1 Test of Parallel Trend Assumption

The validity of DID method hinges on two key assumptions, namely the parallel trend assumption and exogeneity of HSR connections. We graphically illustrate the trends of co-patents between different types of city-pairs. Figure 2 illustrates the trend comparison of different city-pairs.

Figure 2: Trends Comparisons before and after the HSR Openings

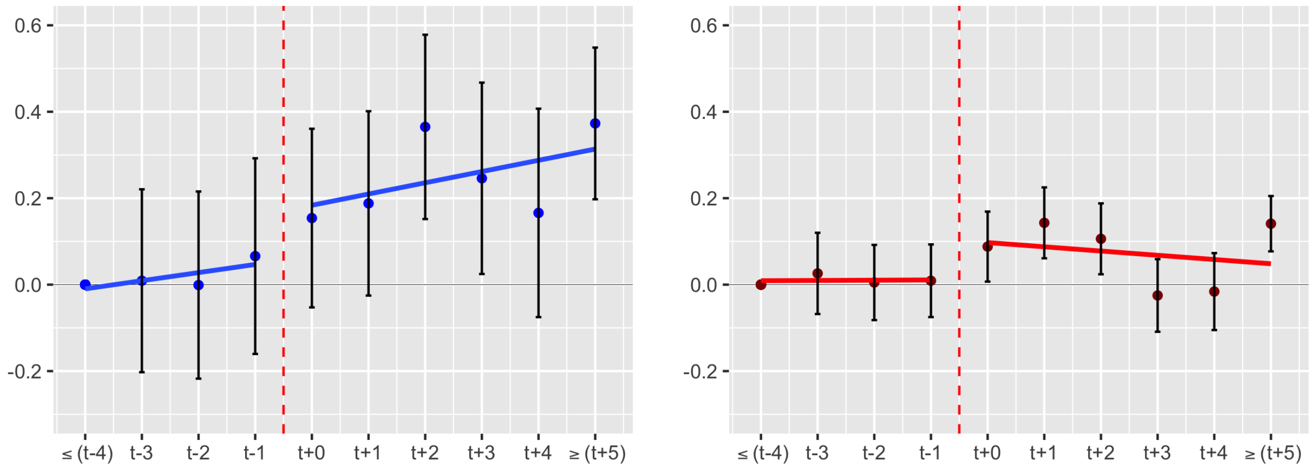


Note: Since HSR connection took place in different years over time, we align the opening year at time t. The red dashed line indicates the event of HSR connection dividing the pre- and post-periods. The left panel compares the connected and the unconnected city-pairs. The right panel compares the connected city-pairs of different distance in-between.

The left panel compares the trend of connected and non-connected city-pairs, and the right illustrates the trends of connected city-pairs of different distance ranges. At a glance, the pre-treatment lines followed a relatively close trend with each other. However, when inspecting more closely, there is a slight divergence visible at year t-1, which also shows up in Figure 3 that there is a slight jump in year t-1. Given that all variables are random, a slight divergence is acceptable. Nonetheless, we argue that the slight divergence in parallel trends is likely the result of the 'step ahead' effect. That is, organizations may move ahead to carry out more collaborative activities in anticipation of HSR connection. As R&D and innovations are long-term projects, in the foresight of better connectivity and more convenient travel, firms may move ahead to increase collaboration with partners that are more accessible in the near future. We argue that the "step-ahead" effect differs from a secular divergent effect and does not carry into the following periods.

For Peer Review Only

Figure 3: The Dynamics of HSR Effects: Co-patents and Partnerships



Note: We run the same fixed-effects regression model with indicator variables corresponding to three years before and 6 years after HSR connection. The left panels reports the regression coefficients of co-patents and the right panel reports the coefficients of the partnerships. The vertical bars represent 90% confidence internal.

To test whether the slight divergence is within statistical tolerance, we construct an event study to investigate the dynamics of HSR effects in specific years before and after connection. Figure 3 illustrates those coefficient estimates for individual years. On the left panel, the blues dots indicate the estimated coefficients of HSR connection on co-patents for city-pairs within 250km. The three years before connection had a weak effect, while the effect of post-connection started to pick up and peaked in year t + 2, two years after connection. The right panel shows the effect on collaborative partnerships. Similar to the effect on co-patents, the pre-connection years showed little effect, while intercity collaborative partnerships started to establish from $t + 0$ to $t + 3$. The results of the event study again confirm that the parallel trend assumption holds and that the increased intercity co-patents and partnerships occur likely as a result of the construction of the HSR network.

Furthermore, we conduct a placebo test to check whether the identified HSR effect could be contaminated by the pre-treatment trend. The results (available in the online Appendix) confirm that the parallel trend assumption required in the DID method is satisfied.

5.2 Test of Endogeneity

Another potential identification issue is endogeneity resulting from reverse causality. If planning of HSR routes were to be based on the expectation that some cities tend to engage more in collaborative activities, then HSR connection would be endogenous due to reverse causality. Following Dong et al. (2019), we use historical rail connection and city-level elevation as instrumental variables (IVs) and adopt a two-stage least square (2SLS) approach to test endogeneity. The results

For Peer Review Only

(available in the online appendix) confirm that findings from our DID analysis are robust. Taken together, the results of trends comparison, event study, and IV regression all confirm that our DID analysis satisfies its key assumptions and that our findings are robust.

5.3 Marketization Index as a Measure of Institutions

In this study, we follow Hong and Su (2013) and use a province-border measure of institutional distance. We find evidence to confirm that institutional distance moderates the positive effect of HSR connection on innovation collaboration between connected city-pairs. To test the robustness of our results, we use the marketization index as an alternative measure of institutional distance. Marketization index (MI) is a frequently used measure of institutional quality in China (Li et al., 2006; Firth et al., 2009). It measures the extent to which Chinese provinces progress toward a fully-fledged market economy under economic reform (Bin et al., 2020). Using MI as an alternative measure of institutional distance, we find consistent evidence (available in the online appendix) with one that uses province-border as a measure of institutional distance. The additional analysis thus confirms that our main thesis regarding the effect of institutional distance remains robust.

5.4 Heterogenous Effect on Cities of Different Sizes

To test the heterogeneity of treatment effect among cities of different sizes, we further conduct a subsample analysis on cities of different sizes. We split Chinese cities into 49 major and 236 small cities. To disentangle the effect of HSR, we separate the observations into three types: major-major, major-small, and small-small. We run sub-sample regressions of the three types of city-pairs (detailed in online Appendix). Table A4 (online Appendix) reports the HSR effects on city-pairs of different size combinations. The analysis reveals three additional intriguing results. First, the most significant HSR effect comes from between major-small city-pairs. HSR connection increases the number of co-patents by 22.6% within 250 km, 13.9% within 600 km, and 33% within the same province for the major-small city-pairs. Second, for large-large city-pairs, the significant HSR effect (20.8 % increase) is only found within 250 km, and the effect is more pronounced (29.4% increase) within the same province. Third, HSR connection has insignificant effect on innovation collaborations in small-small city-pairs.

6 Discussion and Conclusion

In this paper, we investigate the effect of HSR on intercity innovation collaboration. Using the massive construction of the HSR network in China as a quasi-natural experiment with a variety of econometric approaches, we find that HSR connections increase collaboration quantity (co-patents) and quality (value-weighted co-patents) by 26.1% and 28.6% respectively for city-pairs within 250

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk
For Peer Review Only

km. The HSR effect diminishes after 250km and disappears beyond 600km. Institutional proximity positively moderates the HSR effect, i.e., the HSR effect for city-pairs of the same provinces is stronger than for those across different provinces. Further analyses show that the HSR effect on II co-patents is greater than URI co-patents within 250 km, while the HSR effect is stronger for URI than II co-patents within the same province. Our research contributes to the literature on collaboration in several ways.

First, our research provides a more nuanced understanding of the HSR effect on intercity innovation collaboration. Our research investigates inter-organizational collaborations and finds a similar HSR effect on the quantity and quality of co-patenting between connected city-pairs, thus enriching the evidence base of the HSR and innovation collaboration literature. Moreover, extant research is inconsistent on whether HSR has the "polarized-effect" or "leveling-up effect". For example, some studies found that HSR enhances the economy of core cities or large cities at the expense of smaller cities (e.g. Monzón et al., 2013; Ke et al., 2017; Vickerman, 2018). On the contrary, some studies found that HSR creates new locational advantages for small cities (e.g. Sasaki et al., 1997; Chen and Haynes, 2017). Dong et al.'s (2019) research on academic co-publication found that HSR increases co-authors' productivity and cooperation among authors from central and secondary cities. The evidence from our research on inter-organizational collaboration does not dismiss the "polarized effect" of HSR as we find the significant HSR effect on innovation collaboration is only found for large-large city-pairs within 250 km. However, our findings lean more towards the "leveling-up" effect as we find that the HSR effect is more pronounced on co-patenting between major-small city-pairs up to the geographical distance of 600 km. While our research observes the tendency of innovation collaboration between large cities, we nonetheless find that HSR networks help reconfigure the national innovation system by expanding the system's reach to smaller cities.

Second, our research contributes to the understanding of the complementary effect between geographical distance and institutional distance on innovation collaboration. In the limited literature that adopts the definition of institutional proximity at the macro level, Hong and Su's (2013) research implies a substitution effect between geographical proximity and institutional proximity. Marek et al.'s (2017) research a U-shaped effect of institutional distance on inter-regional innovation collaboration. We extend this line of research to account for changes in the infrastructure on collaboration in the case of HSR. We particularly embed our arguments in the decentralization perspective. We find that institutional friction remains persistent even after cities are connected by HSR. As a result, the positive effect of lower travel costs is weakened by persistent institutional friction, suggesting that HSR benefits are moderated among cities across different provinces. Our research thus implies that the impact of HSR on intercity innovation collaboration would be greater if local protectionism in the decentralization system were to be weakened.

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

Third, we enrich the literature of transportation infrastructure and intercity collaboration with empirical evidence that shows that HSR connections affect URI and II collaborations differently.

The findings of this study have practical implications for policymakers. Recent studies suggest intercity collaboration linkages improve cities' innovation capacity (Cao et al., 2021). Hence, to best capitalize on the effect of HSR, policymakers need to pursue a synergetic development plan of transportation and intercity innovation collaboration network. Local governments could work together and toward eliminating the persistent presence of institutional friction that weakens the benefits of HSR connection, especially on URI innovation collaboration, freeing up the flow of knowledge and innovative resource to form a more integrated national innovation system. As HSR connection presents an opportunity for innovators in small cities to form collaborative projects with the major cities where innovative resources are more abundant, the local policymakers should create accommodation and encourage such collaboration with the major cities.

This study has limitations. First, our research only captures the partial effect of HSR connection on innovation collaboration because collaborative innovation activities do not always produce patentable technologies. A comprehensive measurement of collaborative innovation activities, if possible, would improve analyses and estimates. Second, our research does not directly measure the travel cost of HSR relative to other modes of transport. Yet, the question of how HSR saves travel costs to enhance innovation collaboration can be interesting and worth exploring. Third, future work could extend to investigations into how HSR connections affect other forms of intercity open innovation practices, such as intercity technology licensing and joint ventures.

References

Agrawal, Ajay and Avi Goldfarb, "Restructuring Research: Communication Costs and the Democratization of University Innovation," *American Economic Review*, August 2008, *98* (4), 1578–1590.

Bai, Chong-En, Yingjuan Du, Zhigang Tao, and Sarah Y Tong, "Local protectionism and regional specialization: evidence from China's industries," *Journal of international economics*, 2004, *63* (2), 397–417.

Balland, Pierre-Alexandre, Ron Boschma, and Koen Frenken, "Proximity and Innovation: From Statics to Dynamics," *Regional Studies*, June 2015, *49* (6), 907–920.

Bercovitz, Janet and Maryann Feldman, "The mechanisms of collaboration in inventive teams: Composition, social networks, and geography," *Research Policy*, 2011, *40* (1), 81–93.

Bin, Peng, Xiaolan Chen, Andrea Fracasso, and Chiara Tomasi, "Firm employment growth in China: The role of marketization and regional economic factors," *Growth and Change*, March 2020, *51* (1), 402–439.

Boschma, Ron, "Proximity and innovation: a critical assessment," *Regional studies*, 2005, *39* (1), 61–74.

Cao, Zhan, Ben Derudder, and Zhenwei Peng, "Interaction between different forms of proximity in inter-organizational scientific collaboration: The case of medical sciences research

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

For Peer Review Only

network in the Yangtze River Delta region," *Papers in Regional Science*, 2019, *98* (5), 1903–1924.

_ , _ , Liang Dai, and Zhenwei Peng, "'Buzz-and-pipeline' dynamics in Chinese science: the impact of interurban collaboration linkages on cities' innovation capacity," *Regional Studies*, April 2021, pp. 1–17.

Cappelli, Riccardo and Fabio Montobbio, "European integration and knowledge flows across European regions," *Regional Studies*, 2016, *50* (4), 709–727.

Catalini, Christian, Christian Fons-Rosen, and Patrick Gaulé, "How Do Travel Costs Shape Collaboration?," *Management Science*, 2020. Publisher: INFORMS.

Chen, Kang, "Administrative decentralisation and changing state-society relations in china," *International Journal of Public Administration*, 1998, *21* (9), 1223–1255.

Chen, Zhenhua and Kingsley E Haynes, "Impact of high-speed rail on regional economic disparity in China," *Journal of Transport Geography*, 2017, *65*, 80–91.

Davids, Mila and Koen Frenken, "Proximity, knowledge base and the innovation process: towards an integrated framework," *Regional Studies*, 2018, *52* (1), 1–12.

Ding, Xuedong and Jun Li, *Incentives for innovation in China: Building an innovative economy*, Routledge, 2015.

Dong, Xiaofang, Siqi Zheng, and Matthew E Kahn, "The Role of Transportation Speed in Facilitating High Skilled Teamwork Across Cities," *Journal of Urban Economics*, 2019, p. 103212.

Etzkowitz, Henry and Loet Leydesdorff, "The dynamics of innovation: from National Systems and "Mode 2" to a Triple Helix of university–industry–government relations," *Research Policy*, February 2000, *29* (2), 109–123.

Firth, Michael, Chen Lin, Ping Liu, and Sonia M L Wong, "Inside the black box: Bank credit allocation in China's private sector," *Journal of Banking & Finance*, 2009, p. 12.

Fischer, Manfred M, Thomas Scherngell, and Eva Jansenberger, "The geography of knowledge spillovers between high-technology firms in Europe: Evidence from a spatial interaction modeling perspective," *Geographical Analysis*, 2006, *38* (3), 288–309.

Gao, Yanyan and Jianghuai Zheng, "The impact of high-speed rail on innovation: An empirical test of the companion innovation hypothesis of transportation improvement with China's manufacturing firms," *World Development*, 2020, *127*, 104838.

Guigon, Marc., "The perpetual growth of high-speed rail development," *Global Railway Review*, 2020.

Hansen, Teis, "Substitution or overlap? The relations between geographical and non-spatial proximity dimensions in collaborative innovation projects," *Regional Studies*, 2015, *49* (10), 1672–1684.

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

Inoue, Hiroyasu, Kentaro Nakajima, and Yukiko Umeno Saito, *The Impact of the opening of high-speed rail on innovation*, RIETI, 2017.

Jaffe, Adam B, Manuel Trajtenberg, and Rebecca Henderson, "Geographic localization of knowledge spillovers as evidenced by patent citations," *the Quarterly journal of Economics*, 1993, *108* (3), 577–598.

Ke, Xiao, Haiqiang Chen, Yongmiao Hong, and Cheng Hsiao, "Do China's high-speed-rail projects promote local economy?—New evidence from a panel data approach," *China Economic*

For Peer Review Only

Review, 2017, *44*, 203–226.

Lawrence, Martha, Richard Bullock, and Ziming Liu, *China's high-speed rail development* 2019. OCLC: 1101272415.

Li, Hongbin, Lingsheng Meng, and Junsen Zhang, "Why Do Entrepreneurs Enter Politics? Evidence from China," *Economic Inquiry*, July 2006, *44* (3), 559–578.

Marek, Philipp, Mirko Titze, Clemens Fuhrmeister, and Ulrich Blum, "R&D collaborations and the role of proximity," *Regional Studies*, December 2017, *51* (12), 1761–1773.

Maurseth, Per Botolf and Bart Verspagen, "Knowledge spillovers in Europe: a patent citations analysis," *Scandinavian Journal of Economics*, 2002, *104* (4), 531–545.

Monzón, Andrés, Emilio Ortega, and Elena López, "Efficiency and spatial equity impacts of high-speed rail extensions in urban areas," *Cities*, 2013, *30*, 18–30.

Neter, John, Michael H Kutner, Christopher J Nachtsheim, William Wasserman et al., *Applied linear statistical models*, Irwin Chicago, 1996.

North, Douglass C et al., *Institutions, institutional change and economic performance*, Cambridge university press, 1990.

Perkins, Dwight Heald, "Reforming China's economic system," *Journal of Economic Literature*, 1988, *26* (2), 601–645.

Picci, Lucio, "The internationalization of inventive activity: A gravity model using patent data," *Research Policy*, 2010, *39* (8), 1070–1081.

Ponds, Roderik, Frank Van Oort, and Koen Frenken, "The geographical and institutional proximity of research collaboration," *Papers in regional science*, 2007, *86* (3), 423–443. Publisher: Wiley Online Library.

Sasaki, Komei, Tadahiro Ohashi, and Asao Ando, "High-speed rail transit impact on regional systems: does the Shinkansen contribute to dispersion?," *The annals of regional science*, 1997, *31* (1), 77–98.

Scott, W Richard, *Institutions and organizations: Ideas, interests, and identities*, Sage publications, 2013.

Sun, Xiaoqian, Yu Zhang, and Sebastian Wandelt, "Air transport versus high-speed rail: an overview and research agenda," *Journal of Advanced Transportation*, 2017, *2017.*

Torre, Andre and Alain Rallet, "Proximity and Localization," *Regional Studies*, February 2005, *39* (1), 47–59.

Vickerman, Roger, "Can high-speed rail have a transformative effect on the economy?," *Transport Policy*, 2018, *62*, 31–37.

For Peer Review Only

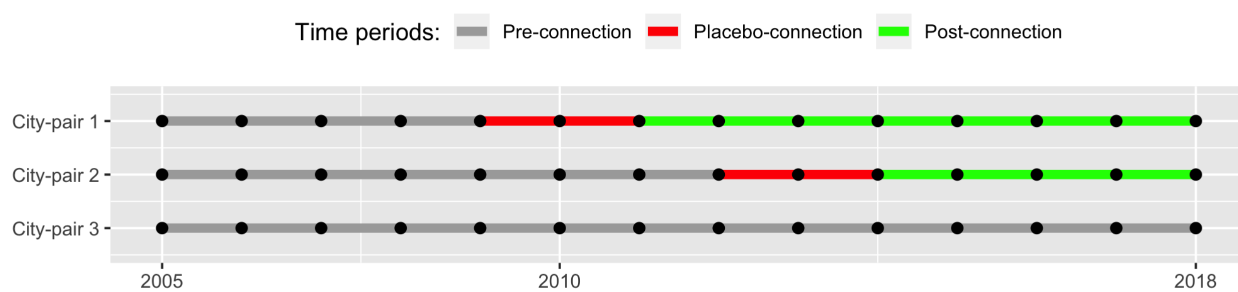
Online Appendix

In this appendix, we report several robustness checks we have carried out. Section 1.1 reports the placebo test to check whether a counter-factual treatment would generate positive and significant effects. Together with the event study, it is to ensure our analysis satisfies the common trend assumption. Section 1.2 reports the robustness check to see our main results hold when we use the marketization index as an alternative measure of institutional distance. Section 1.3 conducts sub-sample analysis and explores the heterogenous HSR effect among cities of different sizes. Section 1.4 reports the instrument variable regression to test the potential endogeneity problem.

1.1 Placebo Test

In conducting a placebo test, we aim to check whether the identified effect could be contaminated by the pre-treatment trend. We create a placebo treatment of HSR connections using two years prior to the actual opening year and remove all observations with actual HSR connections. Figure A1 shows how the placebo variable is created.

Figure A1: Visual Illustration of Placebo Variable Construction



Note: This is a graphical illustration of how the placebo variable is constructed. The X-axis is the time horizon from 2005 to 2018, while the Y-axis is three typical city-pairs. City-pair 1 and 2 are HSR-connected during a year, while city-pair 3 is never connected. To constructed the placebo variable, first, all post-connection period observations, as indicated by the green color, are deleted. Second, a placebo, as indicated by the red color, is created for the connected city-pairs for two periods before the true connection year. If the regression result shows the significance of the placebo effect, then the equal trend assumption is rejected.

Table A1 reports the regression results using placebo variable designed. Column (1) shows that the coefficient of *Placebo* is insignificant at 0.105, suggesting that right before the HSR connection there is no significant trend between the connected and the unconnected. The interaction term of *Placebo* with *Dist.S* suggests between 0 to 250km, the placebo effect is insignificant and with a low positive effect. The interaction term of *Dist.M* suggests that city-pairs between 250 to 600km apart experienced a 27.4% reduction during two years prior to the HSR connection. The interaction term of *Dist.L* is insignificant.

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

Table A1: The Placebo Test

	Dependent Variable: Co-patent Counts	
	(1)	(2)
$Plcebo$	0.105 (0.069)	0.061 (0.087)
$Plcebo \times Dist.S_{(0\sim250km)}$	0.043 (0.103)	
$Plcebo \times Dist.M_{(250\sim600km)}$	-0.206^{**} (0.091)	
$Plcebo \times Dist.L_{(600\sim1000km)}$	-0.035 (0.096)	
$Plcebo \times Distance$		0.00004 (0.0001)
$Plcebo \times SameProv$		0.012 (0.105)
$Control\ Variables$	Yes	Yes
$City, Year\ FE$	Yes	Yes
Observations	55,013	55,013
Akaike Inf. Crit.	81,965.050	82,073.530

Note: There are 23,924 city-pair-year observations were omitted from total 79,058 observations. All 55,013 are non-connected city-pair-year observations.

Overall, the parallel trend required in the DID method is satisfied. For the middle ranged city-pairs, there is a noticeable fall before HSR connection. We argue that it does not change the results because even if the trend for the middle ranged city-pair is to decrease the co-patents, the DID estimate can be interpreted as the lowered bound. Moreover, the parallel assumption on the city-pairs within 250 km holds well and hence the main results are robust.

Column (2) confirms the parallel assumption between the connected and the unconnected and also between city-pairs within and across provinces.

1.2 Marketization Index as a Measure of Institution Proximity

In this study, we follow Hong and Su (2013) and use a province-border measure of institutional friction. It implies that cities belonging to the same province are considered institutionally approximate and incur no institutional friction because they are subject to the same political, legal, and regulatory influences. To test the robustness of our results, we use the marketization index as an alternative measure of institutional friction. Marketization index (MI) is also a frequently used measure of institutional quality in China (Chen et al., 2006; Li et al., 2006; Firth et al., 2009) since it indicates how Chinese provinces progress toward the realization of a fully-fledged market economy under economic reform (Bin et al., 2020). The index is composed of five pillars that reflect the different aspects of the marketization process, namely development of intermediate organization and law, government-market relation, private economic development, product market development, and factor market development (Wang et al., 2017). A province's score in the marketization index is the aggregate score of all sub-indices in five pillars. MI was developed by the National Economic Research Institute (NERI), an influential think tank in China, and the

For Peer Review Only

first MI report was published in 2000. Following Mao and Mao (2021), we calculate the intercity institutional friction (or institutional distance) using the following equation:

$$Institutional.dist = \sum_{k}^{5}[(I_{k,i} - I_{k,j})^2/V_k]/5 \quad (1)$$

where I_k, i is the marketization index k for city i, V_k is the variance of institutional score of kth pillar. As the marketization index is measured at the provincial level, we additionally define Institutional distance between cities of the same province is zero because cities in the same province tend to share the same regulations, policies, and laws. Table A2 presents the scores of marketization index for the provinces and municipalities obtained from the report by Wang et al. (2017). At a glance, the marketization index is positively correlated with the development level in each region.

Table A2: Marketization Index for Provinces and Municipalities

1	Shanghai	9.5	Fujian	8.0	Hubei	6.5	Hebei	6.0	Yunnan	4.9
2	Zhejiang	9.4	Shandong	7.6	Sichuan	6.5	Heilongjiang	5.6	Ningxia	4.7
3	Jiangsu	9.3	Chongqing	7.2	Hunan	6.3	Hainan	5.4	Guizhou	4.5
4	Guangdong	9.0	Liaoning	7.0	Jiangxi	6.2	Shaanxi	5.2	Gansu	4.0
5	Beijing	8.7	Anhui	6.7	Jilin	6.1	Inner Mongolia	5.2	Xinjiang	3.8
6	Tianjin	8.5	Henan	6.6	Guangxi	6	Shanxi	5.1	Qinghai	3.1

Note: The marketization index is the average from 2005 to 2016 for each province and municipality.

As reported in Table A3, in the new regressions, we replace $SamePro$ with $Institutional.Dist$. The regression results in Columns (2), (3), and (4) show that the coefficients of institutional distance are negative and significant, indicating that institutional distance has a negative effect on intercity co-patent. In Column (4), the coefficient of interaction between HSR connection and institutional distance is negative and significant, suggesting that institutional distance constrains the HSR effect. These results are consistent with one that uses province-border as a measure of institutional distance. They thus confirm that our main thesis regarding the effect of institutional distance remains robust even if we use the marketization index as an alternative measure of institutional distance. The caveat of using the marketization index is that it is a measurement at the provincial level. The political distance between cities of the same province is defined as zeros. So the institutional distance here can be interpreted as a combination of provincial marketization index and province-border definition.

It is worth noting that there's difference between the two definitions. The province-border definition disregards the "quality" of institutions, i.e., it does not measure good or bad institutions; instead, it measures whether organizations in different cities are subject to the same administration and hence similar political, economic, and legal environment. As Hong and Su (2013) noted,

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

Table A3: The Baseline Regression (Using Marketization Index as Institutional Distance)

	Dependent Variable: *CoPatent*			
	(1)	(2)	(3)	(4)
Connect	1.974***	0.006	−0.024	0.243***
	(0.059)	(0.043)	(0.056)	(0.069)
Distance	−0.001***	−0.001***	−0.001***	−0.001***
	(0.0001)	(0.00003)	(0.0001)	(0.00004)
Instutional.Dist	0.028	−1.238***	−1.049***	−1.191***
	(0.074)	(0.038)	(0.050)	(0.045)
$Dist.S_{(0\sim250km)}$			0.406***	
			(0.096)	
$Dist.M_{(250\sim600km)}$			0.003	
			(0.078)	
$Dist.L_{(600\sim1000km)}$			−0.011	
			(0.060)	
$Connect \times Dist.S_{(0\sim250km)}$			0.261***	
			(0.075)	
$Connect \times Dist.M_{(250\sim600km)}$			0.146**	
			(0.073)	
$Connect \times Dist.L_{(600\sim1000km)}$			−0.039	
			(0.070)	
$Connect \times Distance$				−0.00004
				(0.0001)
$Connect \times Instutional.Dist$				−0.165**
				(0.069)
CityPair Controls	No	Yes	Yes	Yes
City&Year FE	No	Yes	Yes	Yes
Observations	79,058	79,058	79,058	79,058
Akaike Inf. Crit.	201,826.100	171,405.200	171,173.400	171,299.200

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors are clustered at the city level.

Chinese local governments prefer to match local firms with universities to form collaboration, so as to keep innovative resources within their territory. They often implement policies and regulations to encourage such local preferences. Under such incentives and expectations, innovative organizations under the administration of the same government are more likely to collaborate with each other. In contrast, the marketization index is a measurement of institutional "quality". A higher score of marketization index is considered an indication of a better institutional setting for organizations to carry out economic activities

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

For Peer Review Only

1.3 Heterogenous Effect on Cities of Different Sizes

Table A4: Heterogeneous Effect of HSR Connection on Cities of Different Sizes

	Dependent Variable: Co-patent Counts					
	Major-Major		Major-Small		Small-Small	
	(1)	(2)	(3)	(4)	(5)	(6)
Connect	−0.076	−0.060	−0.031	−0.038	−0.035	−0.037
	(0.065)	(0.087)	(0.055)	(0.066)	(0.165)	(0.174)
$Connect \times Dist.S_{(0\sim250km)}$	0.208*		0.226**		0.248	
	(0.111)		(0.094)		(0.206)	
$Connect \times Dist.M_{(250\sim600km)}$	0.094		0.139**		0.175	
	(0.083)		(0.067)		(0.200)	
$Connect \times Dist.L_{(600\sim1000km)}$	−0.038		−0.051		0.074	
	(0.078)		(0.069)		(0.227)	
$Connect \times Distance$		−0.00001		0.00002		0.0001
		(0.0001)		(0.0001)		(0.0001)
$Connect \times SameProv$		0.294**		0.330***		0.266
		(0.120)		(0.089)		(0.183)
City Controls	Yes	Yes	Yes	Yes	Yes	Yes
City, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,350	14,350	49,140	49,140	15,568	15,568
Akaike Inf. Crit.	54,521.920	54,544.550	98,083.250	98,155.330	15,699.140	15,700.630

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors are reported.

To test the heterogeneity of treatment effect among cities of different sizes, we further conduct a subsample analysis on cities of different sizes. We split Chinese cities into two types, major and small cities. Distinguishing between major and small cities can be challenging since there is no official definition of major or small cities in China. Following previous research (e.g. Chen and Fang, 2018) we use the popular five-tier city classification framework that was developed by Yicai Global, a leading media group in China. It ranks cities in accordance with five dimensions of commercial attractiveness, including the concentration of commercial resources, the extent to which a city serves as a business hub, vitality of urban residents, diversity of lifestyle, and future dynamism. It thus classifies 19 cities as first-tier cities, 30 as second-tier cities, and the rest as tier 3 to tier 5. Following this classification, we define the first and second-tier cities as major cities, and the rest as small cities. There are a total of 49 major cities, and 236 small cities. To disentangle the effect of HSR, we separate the observations into three types: major-major, major-small, and small-small. We run sub-sample regressions of the three types of city-pairs. Table A4 reports the HSR effects on city-pairs of different size combinations. The analysis reveals three additional intriguing results. First, the most significant HSR effect comes from between major-small city-pairs. HSR connection increases the number of co-patents by 22.6% within 250 km, 13.9% within 600 km, and 33% within the same province for the major-small city-pairs. Second,

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk
For Peer Review Only

for large-large city-pairs, the significant HSR effect (20.8 % increase) is only found within 250 km, and the effect is more pronounced (29.4% increase) within the same province. Third, HSR connection has no effect on innovation collaborations in small-small city-pairs.

1.4 Instrument Variable Regression

Our results may be affected by endogeneity that may occur as a result of missing variables or reverse causality. As we have included city and year fixed effect and a number of control variables in our regressions, endogeneity due to missing variables should not be a concern but reverse causality can be. This is because policymakers in China may have planned the HSR network to connect cities with the high potential of future economic connection. If that is the case, the endogeneity problem could create upward bias and the estimates could be spurious. One way to tease out the endogeneity is to use instrument variable, which correlates with the endogenous variable HSR connection but does not directly correlate with the outcome variable, intercity co-patents. Such variables are surely difficult to find. We follow the literature and use two instrument variables, historic rail connection, and city altitude (Baum-Snow et al., 2017; Dong et al., 2019). Historic rail connection is closely correlated to the modern-day HSR layout but is arguably not directly correlated with intercity innovation collaboration today, as Baum-Snow et al. (2017) argued the old rail system served very different functions, such as shipping raw materials and manufactures between larger cities and to provincial capitals according to the dictates of national and provincial annual and five-year plans. We use the Chinese rail system in 1961 as the first instrument variable of modern-day HSR network. The second instrument is geographical elevations of cities; due to the construction cost, cities with higher altitudess are less likely connected to the HSR network.

Table A5: The First Stage Regression of 2SLS

	Dependent variable:
	connect_2018
Elevation.l	−0.00003 (0.00002)
Elevation.s	-0.0002^{***} (0.00001)
Historic.l	0.183^{***} (0.018)
Histroic.s	0.128^{***} (0.012)
Observations	5,647
R^2	0.158

Note: This is the first stage regression of 2SLS. The endogenous variable "connect2018" is regressed on all the instrument variable and exogenous variable. In this table, we only show the coefficients of the four instrument variables.

Due to that the IVs are time-invariant—that is, the instruments can only predict whether

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk

For Peer Review Only

cities are connected by 2018 but not when—we use a long-difference model to examine the effects of HSR-connection on intercity innovation collaboration. The long-difference model converts the panel data into a cross-sectional one by taking the logarithmic difference of co-patent count between 2005 and 2018[1]. The first stage is to regress the endogenous variable, $Connect_{ij}$, on the instrument variable and exogenous variable as shown in Table A5.

Due to the dyadic nature of our observation, each observation involves two cities. Each two cities are arranged in their GDP size and defined as the larger or smaller city, as indicated by the suffix ".L" and ".S". The first stage result shows that for the larger city, elevation does not predict the HSR connection in 2018 while the elevation of smaller cities is negatively correlated with the prospect of HSR connection. That means the policymaker has planed the HSR network to connect the larger cities regardless of the geographical condition, while a harsh geographical environment could impede the HSR connection for the smaller cities. Historical rail connections positively predict the modern-day HSR connection for both smaller and larger cities. Geographical elevation and historic connection are strong instruments as indicated by the significant coefficients.

Table A6: The Long Difference OLS and IV regression Results

	Dependent variable:			
	Copatent count (2005-2018)		Collaboration partners (2005-2018)	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Connect	0.151*** (0.049)	−0.040 (0.191)	0.092*** (0.036)	−0.130 (0.139)
$Connect \times Dist.S_{(0\sim250km)}$	0.310*** (0.104)	0.655** (0.300)	0.207*** (0.076)	0.433** (0.218)
$Connect \times Dist.M_{(250\sim600km)}$	−0.126 (0.078)	0.173 (0.229)	−0.092 (0.057)	0.083 (0.166)
$Connect \times Dist.L_{(600\sim1000km)}$	−0.088 (0.079)	0.077 (0.219)	−0.010 (0.057)	0.207 (0.159)
Observations	5,647	5,647	5,647	5,647
R^2	0.246	0.243	0.276	0.271

Note: The table compares the OLS and IV regression results. It only presents the endogenous variables.

Table A6 reports the 2SLS long-differecnce regerssion results. Columns (1) and (2) show the effects on intercity co-patent count and Columns (3) and (4) are on collaborative partnerships. Column (1) presents the OLS results and it shows that co-patents in city-pairs that are HSR-connected tend to grow by 31% for cities within 250 km. For city-pairs that are beyond that range, they expect to grow by 15.1% in co-patents. This finding closely aligns with our previous results using Negative Binomial panel regression. Column (2) shows the IV 2SLS results, where the standard errors are inflated as expected. The coefficient of HSR connection within 250km remains

[1]To implement a Two-Stage Least Square approach means we cannot have Negative Binomial regression. So instead we use OLS and take the logarithmic of the outcome variable. Following Dong et al. (2019), because there are many zero we use log(x + 1) method.

http://mc.manuscriptcentral.com/cres Email: cres-peerreview@journals.tandf.co.uk
For Peer Review Only

significant and changes to 0.655, suggesting that the IV result generates an unbiased estimate higher than the OLS result. The same applies to collaborative partners, the HSR effect increases from 0.207 in OLS estimate to 0.433 IV estimate. Higher IV estimates echo Dong et al.'s (2019) research, where they also find higher IV coefficients than OLS estimates using historic and urban geographics as an instrument for HSR connection. The interpretation could be that policymakers preferred equitable development and planned the HSR to connect less developed cities. Again, the IV regression results reaffirm the robustness of our findings, confirming that our main results are not subject to the influence of endogeneity in terms of upward bias.

For Peer Review Only

References

Baum-Snow, Nathaniel, Loren Brandt, J Vernon Henderson, Matthew A Turner, and Qinghua Zhang, "Roads, railroads, and decentralization of Chinese cities," *Review of Economics and Statistics*, 2017, *99* (3), 435–448.

Bin, Peng, Xiaolan Chen, Andrea Fracasso, and Chiara Tomasi, "Firm employment growth in China: The role of marketization and regional economic factors," *Growth and Change*, March 2020, *51* (1), 402–439.

Chen, Gongmeng, Michael Firth, Daniel N Gao, and Oliver M Rui, "Ownership structure, corporate governance, and fraud: Evidence from China," *Journal of corporate finance*, 2006, *12* (3), 424–448.

Chen, Yang and Zheng Fang, "Industrial electricity consumption, human capital investment and economic growth in Chinese cities," *Economic Modelling*, 2018, *69*, 205–219.

Dong, Xiaofang, Siqi Zheng, and Matthew E Kahn, "The Role of Transportation Speed in Facilitating High Skilled Teamwork Across Cities," *Journal of Urban Economics*, 2019, p. 103212.

Firth, Michael, Chen Lin, Ping Liu, and Sonia M L Wong, "Inside the black box: Bank credit allocation in China's private sector," *Journal of Banking & Finance*, 2009, p. 12.

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

Li, Hongbin, Lingsheng Meng, and Junsen Zhang, "Why Do Entrepreneurs Enter Politics? Evidence from China," *Economic Inquiry*, July 2006, *44* (3), 559–578.

Mao, Qiliang and Xianzhuang Mao, "Cultural barriers, institutional distance, and spatial spillovers: Evidence from regional industrial evolution in China," *Growth and Change*, July 2021, p. grow.12527.

Wang, Xiaolu, Gang Fan, and Jingwen Yu, "Marketization index of China's provinces: NERI report 2016," *Social Sciences Academic Press: Beijing, China*, 2017.

For Peer Review Only