Knowledge Spillovers from Public Sector: Evidence from Innovation Cities in South Korea

Manho Kang[*†]

Georgia Institute of Technology

Abstract

This paper investigates knowledge spillovers from public sector facilitated by regional development policies focusing on South Korean Innovation City project, which relocated public agencies from Seoul to provincial regions. Detailed patent data is employed to distinguish the direct impact from spillovers, to measure the precise magnitude of shocks, and to examine the scope of spillovers. Additionally, a winner-loser comparison is conducted to mitigate potential endogeneity concerns. The empirical findings reveal increased innovation in Innovation Cities, driven both by direct and spillover effects. Importantly, spillovers are stronger in already innovative regions and limited to technologically close fields and geographically proximate regions.

Keywords: Knowledge spillover, regional development policy, winner-loser comparison, Innovation City, innovation, patent, South Korea

JEL Codes: R11, R12, R58, O33, O38, N75

[*]I am grateful to David Hummels, Yasusada Murata, Maurizio Zanardi, Reshad Ahsan, Jee-Hyeong Park, Sunhyung Lee, Seunghoon Lee, Jaerim Choi, Jay Hyun, Sewon Hur, and participants in the North American Meeting of the Urban Economics Association, Midwest International Trade Conference, and Southern Economic Association meeting for their invaluable comments and suggestions.

[†]E-mail: manho.kang@gatech.edu.

1 Introduction

Economic activity is spatially concentrated. It is widely accepted that the positive externalities of agglomeration play an important role in concentration, though the specific mechanisms are still in question. One of the candidates is knowledge spillovers, which yield positive intellectual externalities both through formal and informal interaction within locality, and therefore improve productivity. Empirical evidence suggests that an increased interaction through new infrastructure, including the improvement of roads (Agrawal et al., 2017), airline proximity (Giroud, 2013), and high-speed railway (Wang and Cai, 2020; Hanley et al., 2022), which effectively decreases distance between places, improves productivity or increases innovation, which indirectly implies the existence of knowledge spillover effects. Studies also indicate that knowledge spillovers and the benefits of agglomeration attenuate sharply in distance by investigating the spatial concentration of industries (Rosenthal and Strange, 2001, 2003; Arzaghi and Henderson, 2008). However, more direct causal evidence of local knowledge spillovers is less abundant for two reasons. First, people, firms, and other entities choose their best location endogenously. This makes it difficult to evaluate the causal effect of agglomeration on knowledge spillovers because finding appropriate counterfactual is not straightforward due to the endogeneity. Second, it is not clear how to measure knowledge production and its spillovers.

Despite these challenges, a comprehensive investigation is necessary, given its importance not only to economists but also to policymakers, as regional development policies involve substantial public investments and subsidies aiming to boost economic growth, to reduce regional disparities, or to build a next Silicon Valley. These programs arguably have become a new form of industrial policy and are widely implemented globally. For instance, the US federal and local governments have spend around 95 billion dollars per year on place-based policies in the first decade of the 21st century dwarfing the unemployment insurance program (Kline and Moretti, 2014b), and around 32 billion euros are allocated to the European Regional Development Fund between 2021 and 2027. Therefore, it is crucial for policymakers and taxpayers to understand whether regional development policies are effective and how to design more efficient policies. To address these questions focusing on knowledge spillovers, this paper employs four strategies.

First, to overcome the endogeneity issue, a quasi-experimental increase in local agglomeration is investigated. In 2003, South Korean government announced plans to relocate public agencies including state-owned enterprises, government-funded research institutes, and government affiliated organizations (henceforth, relocated agencies) from Seoul metropolitan area to provincial regions to promote balanced regional growth. Which public agencies to relocate was determined by the central government in 2005, followed by the local governments' selection of location in the same year. The relocation of 112 public agencies and 41,364 jobs was originally scheduled for completion by 2012, but the relocation started in 2012 and concluded in 2019. Since the decision of relocation was not made by relocated agencies, but by central and local governments to promote balanced growth, and since whether, when, and where to relocate was influenced by a series of non-economic factors as elaborated in Section 3, this Innovation City Project provides a distinct opportunity to study the spillover effects of regional development policies suffering less from the endogeneity issue. Moreover, a winner-loser comparison is conducted using the information about other candidate municipalities that were not selected as Innovation Cities, strengthening a causal impact of local agglomeration on local knowledge spillovers.by setting a more appropriate control group as in Greenstone et al. (2010).

Second, to measure the production of knowledge, the universe of South Korean patent data is employed. Specifically, the number of patent applications is aggregated at the municipality-level to capture local knowledge production and to examine the impact of relocation on local innovation. In doing so, since patenting in Innovation Cities automatically increases as public agencies move in, it is important to distinguish the direct impact of relocation from its spillover effects. Therefore, patents are classified by the relevance with the relocated agencies. The mechanical effect of relocation is captured by patents applied by relocated agencies by themselves (solo work), whereas the spillovers are measured with patenting related to local agencies. Local agencies' patenting is decomposed further to the number of joint patent applications by local agencies and relocated agencies (co-work), which reveals the direct spillovers between relocated and local agencies through collaboration, and applications independently submitted by local agencies (independent work), which involves more indirect channel.

Third, to capture the effective magnitude of relocation of public agencies and its impact precisely, a time-varying continuous measure of shock is developed. The Innovation City project involves an econometric issue known as the multiple treatments of varying intensities problem. More specifically, public agencies with heterogeneous innovation capacity, and therefore heterogeneous potential for knowledge spillovers, did not relocate to Innovation Cities at once. Therefore, Innovation Cities experienced multiple shocks with heterogeneous magnitude in a staggered manner. To deal with this problem, the number of patents each agency applied for prior to relocation is explicitly considered to proxy their innovation capacity. Then, the timing of their relocation is taken into account to construct the accumulated innovation capacity relocated to Innovation Cities. This measure effectively captures the heterogeneous and gradual impact that each Innovation City experienced.

This is an important benefit of analyzing the relocation of public agencies because the pre-relocation information of relocated agencies allows to construct a time-varying treatment intensity variable, which is not available in other regional development policies examined in the literature.[1] Moreover, this shock measure can be used to compute a local *innovation multiplier*, which shows how many patents are produced when one potential patent is relocated to Innovation Cities. This innovation multiplier informs the magnitude of spillovers, and therefore can be used to evaluate the effectiveness of policies. To my knowledge, this is the first trial to investigate the local innovation multiplier of regional development policies.

[1] For instance, the construction of new universities Andrews (2023) and factories Greenstone et al. (2010) have been examined for clean identification using a winner-loser comparison. However, due to the lack of pre-establishment information, the magnitude of shocks cannot be as precisely measured as this paper.

Finally, to refine the existence, importance, and scope of knowledge spillovers, whether the spillover effects are stronger in technologically similar fields and physically proximate regions is investigated, leveraging a wealth of information in patent data. More specifically, using the technology field and the location of patents, local innovation and the relocated innovation capacity are measured at the municipality-field-level. Then, how local innovation response to the relocated innovation capacity within the same field differs from the response to the relocated innovation capacity in other fields is investigated. If knowledge spillovers are present, they are expected to be stronger in the same technology field where relocated agencies are actively engaged because it is easier for innovators in the similar field to collaborate or learn from each other. In contrast, if other factors that coincide with the relocation, such as improvement in infrastructure, are more important drivers, then the change in local innovation should not be limited to the fields in which relocated agencies innovate.

Also, to examine the spatial scope of spillovers beyond Innovation Cities, the magnitude of innovation capacity relocated to each municipality's neighborhood for each technology field is measured using the distance between each municipality and Innovation Cities. Then, whether these innovation capacity relocated to each municipality's neighborhood affects local innovation is examined at the municipality-field level for different levels of distance. Again, if knowledge spillovers are important drivers of the change in local innovation, the impact is expected to be stronger in technologically similar fields, whereas other factors may impact other technology fields as well. At the same time, since interactions between municipalities are expected to decrease in distance due to the traveling cost, the spillover effects beyond Innovation Cities are likely to be diminishing in distance if they exist.

The empirical evidence can be summarized as follows. First, the relocation of public agencies increases the total number of patent applications in Innovation Cities. This increase includes a mechanical relocation of relocated agencies' solo work to Innovation Cities, and an increase in co-work by local agencies and the relocated agencies, which reveals increased interactions and spillovers. Interestingly, even though relocated agencies' solo work decreases post-relocation compared to pre-relocation, the increase in co-work between local agencies and relocated agencies offsets the loss of solo work so that relocating one potential innovation to Innovation Cities generates more than one innovation in Innovation Cities. However, local agencies' independent innovation does not show a statistically significant increase, which may imply a potentially limited scope of spillovers.

Second, the impact is heterogeneous in that municipalities that were more innovative before relocation show a larger increase in innovation. Remarkably, local independent innovation, which shows a muted response on average, dominantly drives this stronger response. It could reveal stronger spillovers from relocated agencies, but the second-round spillovers between local agencies may also contribute to this larger response. Local innovators in regions with better initial innovation capacity, potentially implying a well-established network and more active interaction between innovators, exhibit stronger effects, which is indeed important in establishing a self-sufficient innovation cluster. In contrast, this type of heterogeneous response is not observed when the size of shock is larger. Economics literature has asked whether a so called "big push" strategy is needed, which relies on the idea of threshold effects.[2] However, in terms of knowledge spillovers and innovation, at least in the context of the Innovation City project, the initial condition is more important than the size of shock.

Third, investigating the change in local innovation within the same technology field and across different technology fields, the municipality-field level analysis reveals that an increase in local innovation is concentrated on the same field. Cross-field effects are not found or economically not meaningful, highlighting the importance of the knowledge spillover channel. In addition, positive spillover effects beyond Innovation Cities are found but limited to very close regions indicating that knowledge spillovers are geographically localized. As expected, the impact of relocation on local innovation is decreasing in economic distance, captured by the technological and geographical proximity, emphasizing the existence, importance, and limited scope of knowledge spillovers.

[2] This idea goes back to Rosenstein-Rodan (1943) and Murphy et al. (1989). See Arzaghi and Henderson (2008), Kline and Moretti (2014a), and Gross and Sampat (2023) for more recent discussion.

These findings underscore several meaningful implications. To begin with, despite substantial government expenditures aimed at fostering innovation clusters and promoting regional growth, it has not been fully understood how to evaluate the efficiency of those place-based policies and their impact on innovation. The concept of local innovation multiplier or the estimated multipliers can be informative for planning and evaluating place-based policies.[3] Although further investigation is needed to measure the value of innovation for a rigorous cost-benefit analysis, it cannot be completely done without information about how local innovation has changed or would change as a result of policies.

Moreover, the observed heterogeneous responses indicate where public investments or subsidies should target. Policymakers should weigh the existing innovative capacity of a region to accelerate local innovation, as regions with higher initial innovation capacity are more likely to experience stronger effects. It is important to acknowledge that innovation is not the only outcome to be considered by policymakers. However, if governments aim to expedite local innovation outside an overly concentrated area concerning regional disparity, an important concern in many countries, directing support to a smaller number of regional innovation centers would be more cost-efficient than evenly distributing limited resources.

Lastly, the evidence of localized knowledge spillovers within the same technology field provides insight into why innovation agglomerates not only spatially but also technologically. If cross-field spillovers were as influential as within-field spillovers, innovation clusters might exhibit similar technological compositions. However, this is not what we observe in the real world. Semiconductor research centers are concentrated in the Silicon Valley in California, the Hsinchu Science Park in Taiwan, and the Hwaseong semiconductor cluster in South Korea, while Boston-Cambridge or "Route 128" corridor is known as a cluster for biotechnology and healthcare innovation. The importance of knowledge spillover in innovation, coupled with stronger within-field spillover effects, results in a pronounced concentration of innovation both spatially and technologically.

[3] Admittedly, local innovation multipliers estimated in this paper may be unique to the Innovation City project. Nevertheless, they could serve as an initial reference for engaging in policy discussions.

2 Related Literature

Broadly speaking, this paper investigates the intersection of three lines of literature. The first strand of literature on regional development policies studies the impact of large scale infra structure development (Kline and Moretti, 2014a; Glaeser and Gottlieb, 2008), place-based tax incentives or subsidies aimed at attracting investments to specific districts including enterprise zones (Neumark and Kolko, 2010), Empowerment Zones (Busso et al., 2013), and more under different names in many countries (Givord et al. (2013) for France, Wang (2013) and Lu et al. (2019) for China) mostly on labor market outcomes such as employment, wages, and income.[4] The concept of local employment multiplier, which explores how changes in one type of local employment affects the other types of employment in the same area, explored in this literature (Moretti, 2010; Moretti and Thulin, 2013; Faggio and Overman, 2014; Faggio, 2019; Jofre-Monseny et al., 2020; Becker et al., 2021), is adopted in the current paper and extended by shedding light on innovation instead of labor market consequences, complementing the next line of research on knowledge spillover effects.

The existence of knowledge spillover effects and their geographical localization is not new to the literature.[5] However, although knowledge spillover is one of the theoretical basis for place-based policies, direct causal evidence of knowledge spillovers has not been actively explored. To overcome endogeneity concern that many early works are not free from, more recent work takes advantage of the quasi-experimental variation. One of the examples is the establishment of universities. In addition to the exogeneity of shocks, it has advantages in exploring the knowledge spillover effects since universities generate new knowledge. For instance, Andersson et al. (2009) show that the Swedish university decentralization policy has positive impact on local innovation, which sharply attenuates with distance. Similar increase in local innovation is found in Italy (Cowan and Zinovyeva, 2013), Switzerland (Pfister et al., 2021), and in the United States (Andrews, 2023).

[4] For a comprehensive review, see Kline and Moretti (2014b) and Neumark and Simpson (2015).

[5] See, for example, Jaffe (1986), Jaffe (1989), Jaffe et al. (1993), Rosenthal and Strange (2001), Ellison et al. (2010), Murata et al. (2014), Billings and Johnson (2016), and Buzard et al. (2020) among others.

However, these works tend not to distinguish the direct activities of universities from the spillover effect on nearby research-intensive industry including the effect through producing higher productivity graduates. This paper complements these approaches by analyzing a distinct policy that relocated pre-existing innovation capacity, which allows a more thorough investigation. The precise measurement of shocks and the technology field that relocated agencies engaged in before the relocation enable to scrutinize the existence, significance, and the scope of knowledge spillover effects separately from direct impact.

It also adds to the large literature on the role of public sector on innovation. Beyond the already mentioned impact of university on innovation,[6] the role of public R&D policies on private innovation (see David et al., 2000; Hall and Van Reenen, 2000; Becker, 2015, for surveys), and the impact of other regulations and policies[7] have been widely studied. However, although public sector generates new knowledge,[8] and despite the location of public agencies is a powerful policy instrument, economists are still lack of research on the knowledge spillovers that relocated public agencies generate.[9] One of the exceptions is Schweiger et al. (2022) who investigate the construction of Science Cities in Soviet Russia and the relocation of scientists to newly established research institutes in those cities. This paper complements their approach by measuring the magnitude of shocks precisely and considering the scope of spillovers by technological similarity equipped with detailed information in the patent data, all of which refine the mechanism.

[6]Not only opening universities but also changing the research capacity of existing universities can impact innovation (Kantor and Whalley, 2014, 2019). See Trajtenberg et al. (1997), Adams (2002), and Xue (2022) for the role of academic research on corporate innovation.

[7]See Jaffe and Palmer (1997), Kneller and Manderson (2012), Aghion et al. (2016), and Calel (2020) for environmental regulations; Gilson (1999), Marx et al. (2009), Belenzon and Schankerman (2013), and Matray (2021) for business laws; Kerr and Lincoln (2010), Hunt and Gauthier-Loiselle (2010), Moser et al. (2014), and Clemens et al. (2018) for immigration policies; and Bustos (2011), Bloom et al. (2016), Autor et al. (2020), and Kang (2023) for trade policies.

[8]For instance, see Jaffe et al. (1998) for NASA and other U.S. federal labs, and Abbate (2000) for the role of U.S. military in the invention of the internet.

[9]Public sector has been relocated in many countries. For the labor market consequences of relocation, see Faggio and Overman (2014) and Faggio (2019) for the United Kingdom, Becker et al. (2021) for Germany, and Jeon and Lee (2021), Lee et al. (2023), and Seo and Kwak (2024) for South Korea.

3 Background

The rapid growth and industrialization of South Korea after the 1960s was supported by the industrial policies represented by the "selection and concentration" strategy to maximize the efficiency to use scarce resources. It allowed the country to grow out of poverty in an unprecedented pace but accelerated the regional concentration to Seoul metropolitan area, the capital region, at the same time. As of 2000, 46.3% of the population, 47.2% of GRDP, 75.3% of patent applications, and 91.0% of top 100 firms were concentrated in Seoul metropolitan area, which accounts for only 12.6% of South Korean area.[10]

Concerning this regional inequality, the 16th President of South Korea, Roh Moo Hyun, made a commitment to promote balanced regional development during his election campaign. However, the outcome of the presidential election remained uncertain until the voting day due to a series of unexpected events. Being nominated as the ruling party's presidential candidate in May 2002, Roh held a slight lead over his major rival, Lee Hoi-chang, who had contested in the previous presidential election. However, in June 2002, the FIFA World Cup took place in South Korea, and surprisingly, the South Korean national soccer team reached the semi-final, even if it had never won a single game in previous World Cups.

After the World Cup, Chung Mong Joon, who played a significant role in organizing the World Cup as FIFA's vice president, emerged as a competitive candidate for the presidential election, gaining traction from the accomplishment of Korean soccer team. Lee Hoi-chang and Chung Mong Joon held the lead over Roh Moo Hyun until one month before the election. However, as the presidential election drew nearer, Chung Mong Joon and Roh Moo Hyun reached an agreement on the candidate unification, and Chung resigned. This allowed Roh Moo Hyun to surpass Lee Hoi-chang in opinion polls, primarily by attracting supporters of Chung, who were relatively more conservative than Roh's supporters but more liberal than Lee's supporters. However, on December 18th, the day before the presidential election,

[10] Sources: Statistics Korea; Korean Intellectual Property Organization; and Korean Ministry of Land, Infrastructure, and Transportation.

Chung Mong Joon announced the withdrawal of his support for Roh, causing astonishment among those who favored Roh due to Chung's backing. In the end, Roh won with a margin of 2.3 percentage points, but the election outcome remained uncertain until the voting day.

Winning the election, the Roh administration announced guidelines for the relocation of public agencies including state-owned enterprises, government-funded research institutes, and government affiliated organizations outside the capital region. In 2004, they made public the Basic Principles and Implementation Direction of Relocation, which conceptualized the Innovation City as a city that facilitates collaboration and networking between relocated agencies, enterprises, universities, and research institutes supported by the innovation-friendly environment. The size of cities was planned to house 20,000-50,000 residents including 2,500-4,000 employees of relocated agencies and relevant industries.

Since the Innovation City project was a part of the balanced national development strategy, it was planned to develop one Innovation City per one province except Seoul metropolitan area (Seoul, Incheon, and Kyeonggi-do), Daejeon, and Chungcheongnam-do. Seoul metropolitan area was automatically excluded since public agencies were moving out of the region, whereas Daejeon and Chungcheongnam-do were excluded since Daejeon had the second government complex, and Roh administration planned to construct a new administrative capital in Chungcheongnam-do.[11]

In addition to this "one Innovation City one province" rule, the size and the number of public agencies allocated to each province were also emphasized since balance and equality were important determinants, which incurred political conflicts and the change in original plans. For instance, Chungcheongbuk-do was not considered as a province to relocate public agencies in the original project since it is close to a planned new administrative capital. However, since Korean Constitutional Court ruled that the Special Act for the Construction of New Administrative Capital was against the constitution in 2004, 12 public agencies were

[11] Roh administration's regional balance policy consisted of two major pillars: Innovation Cities and a new administrative capital. It was planned to relocate administrative division, legislative division, judicial division, and the constitutional court to the new administrative capital.

assigned to Chungcheongbuk-do to compensate its loss.

In 2005, as the central government finalized the guidelines on the site selection, local governments constituted the site selection committee to determine the location of Innovation City within the region based on the guidelines.[12] Since Gwang-ju and Jeollanam-do agreed to develop one Innovation City together, 10 Innovation Cities were selected among 86 candidates, which span 14 municipalities. However, even after the site selection was complete, the Innovation City project kept changing. For instance, Korea Land Corporation (KLC) and Korea National Housing Corporation (KNHC) were planned to relocate to Kyeongsangnam-do and Jeollabuk-do, respectively. However, as a part of the government-led state-owned enterprise advancement plan, KLC and KNHC were merged to Korea Land and Housing Corporation (LH) in 2009. After two years of conflict between two provinces to attract LH, one of the largest relocating agencies, it was determined to relocate LH to Kyeongsangnam-do. To offset the loss of Jeollabuk-do, the government decided to relocate National Pension Fund, which was initially assigned to Kyeongsangnam-do, to Jeollabuk-do in 2011.

Moreover, the Innovation City project was reconsidered by the Lee Myung-bak administration, which inherited the Rho administration, since the Lee administration focused more on the deregulation of Seoul metropolitan area and the privatization of state owned enterprises. Eventually, as local governments and politicians protested strongly against this action, the relocation started in 2012 and completed in 2019, 7 years later than originally planned, and 112 public agencies with 41,364 employees relocated to 10 Innovation Cities.[13]

Considering the relatively weak emphasis on the economic rationale of the Innovation City project, the unexpected introduction and the frequent modification of original plans, the delayed timing of relocation, and the mandated physical relocation, the Innovation City project in this paper is regarded as quasi-experimental, and the relocation of agencies to Innovation Cities are considered as exogenous shock to municipalities throughout the paper.

[12] Appendix 1 shows the selection criteria of Innovation City, which includes various non-economic factors.

[13] The number of public agencies relocated to each province/metro city is: Busan (13), Daegu (10), Gwangju-Jeollanam-do (16), Ulsan (9), Gangwon-do (12), Chungcheongbuk-do (11), Jeollabuk-do (12), Kyeongsangbuk-do (12), Kyeongsangnam-do (11), Jeju (6).

4 Data

4.1 Data Sources

South Korean municipality-level innovation dataset spanning 17 years (2003-2019) is constructed in this paper. The period of interest is set between 2003 and 2019 since the Innovation City project was introduced by the Roh administration in 2003, and the relocation was complete in 2019. The universe of Korean patent data, which is the measure of innovation in this paper, is sourced from Korea Intellectual Property Rights Information Service (KIPRIS). Each patent has unique application number, the name and the address of applicants with IDs, and technology classification among others. Relocated agencies' patents are identified by matching their corporation registration numbers and business registration numbers to patent applicant IDs, and the reported address of applicants is used to assign patents to municipalities. When multiple applicants from different municipalities apply for a patent jointly, the patent is assigned to the first applicant's municipality.[14] Correcting errors, typos, and misreporting, the municipality-level location of 2,032,965 out of 2,032,989 patents filed by domestic applicants are identified between 2003 and 2019.

Information about the list of Innovation Cities, relocated agencies, and the year of their relocation is sourced from the official website of the Innovation City project,[15] and the information about other candidate municipalities of Innovation Cities is requested to local governments and obtained per Official Information Disclosure Act for a winner-loser comparison. All local governments provided information about other candidate municipalities, and four of them clarified runner-up candidates.

For control variables, municipality-level population and the number of four-years universities are sourced from Statistics Korea. Municipality-level employment information is constructed using South Korean Census on Establishments, which contains the establishment-level employment by industry and municipality.[16] The distance between municipalities and

[14] Between 2003 and 2019, the average number of applicants per patent is 1.15.

[15] https://innocity.molit.go.kr

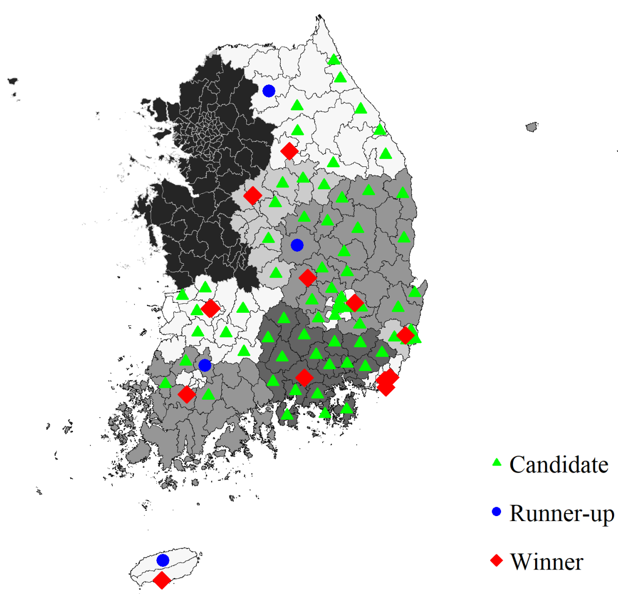
[16] The changes in industry classification over the sample period are harmonized using the 9th revision

Innovation Cities is measured as the linear distance between the centroid of municipalities and the centroid of relocated agencies in each Innovation City. To reflect the change in administrative district, all municipality-level data are aggregated to a larger region when mergers or splits occurred during the sample period. For instance, since Changwon, Masan, and Jinhae merged in 2010, they are aggregated and considered as one municipality even before 2010. Similarly, Cheongwon and Cheongju, Namjeju and Seogwipo, Bukjeju and Jeju, Nonsan and Gyeryong, Goesan and Jeungpyeong are aggregated respectively. Yeongi is regarded as Sejong for the entire sample period.

4.2 Data Description

Figure 1 shows the location of Innovation Cities and other candidates. Reflecting the "one Innovation City in one province" rule, Innovation Cities represented by red diamonds are distributed across 10 provinces outside the Northwest region in black color. Blue dots show the location of runner-up candidates, and green triangles represent other candidates.

Figure 1: Location of Innovation Cities

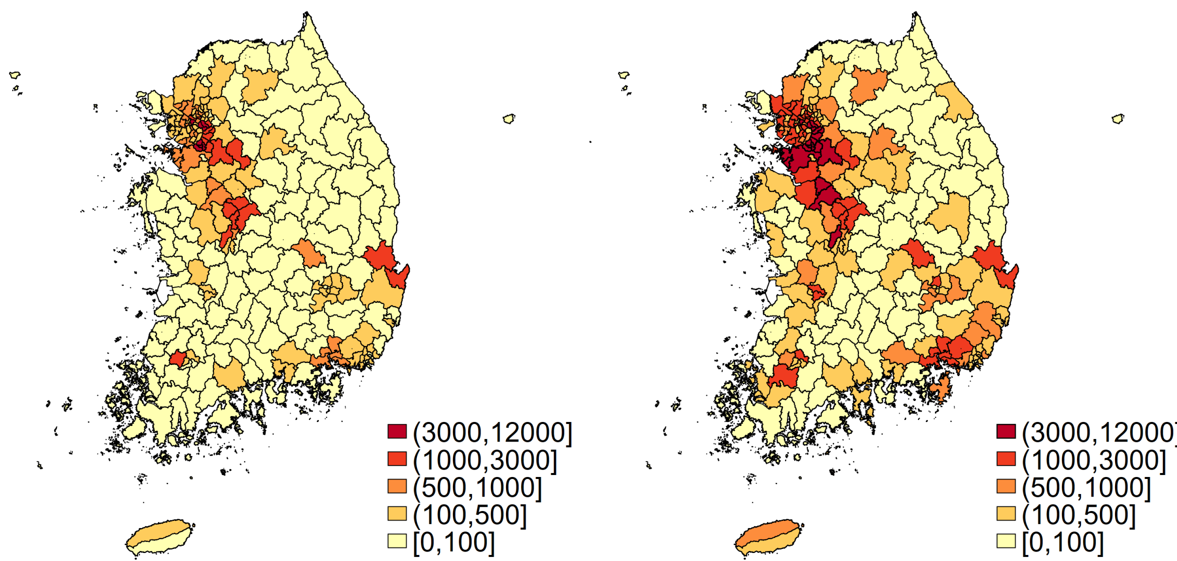


of the Korean Standard Industry Classification (KSIC) using the concordance table provided by Statistics Korea. When necessary, industries are categorized by six large sectors: agriculture, fishery, and mining; manufacturing; construction; personal services; business services; others. Appendix 2 shows specific industries categorized to each sector.

Figure 2 shows how the number of patent applications and its regional distribution evolve from 2003 to 2019. The left map shows that patent applications in 2003 are geographically concentrated in the Northwest region including Seoul metropolitan area. Southeast coast is another region active in innovation, though it is not comparable to Northwest region. The right map shows the number of patent applications in 2019. Compared to the left map, two things are noteworthy. First, patent applications increase in many regions. Second, while the dominance of Northwest region continues, several new innovation centers emerge. Reflecting this dispersion, the share of patent applications of Seoul metropolitan area decreased from 75.8% to 62.7% between 2003 and 2019.[17]

Figure 2: The number of patent applications

(A) Patent applications in 2003 (B) Patent applications in 2019



To explore the emergence of new clusters further, more careful investigation is needed for two reasons. First, the relocation of public agencies automatically increases patent applications in Innovation Cities simply by changing their address from Seoul metropolitan area to Innovation Cities. Therefore, it is necessary to distinguish this mechanical increase through relocation from its spillover effects. In this regard, I classify patent applications into

[17] The share of the Northwest region (Seoul metropolitan area, Chungcheongnam-do, and Daejeon) decreased from 82.6% to 73.4% between 2003 and 2019.

relocated agencies' applications that are not joint-applied with local agencies (solo work), joint applications by relocated agencies and local agencies (co-work), and other applications independently submitted by local agencies (independent work). By doing so, the mechanical and the direct impact of relocation is captured by the change in the solo work, whereas the spillover effect is captured by the change in the co-work and the local independent work. More specifically, an increase in the collaboration between relocated agencies and local agencies is considered as more direct spillover effect, whereas an increase in local independent innovation, for instance due to the better access to knowledge,[18] is thought to more indirect.

Second, since endogenous selection of Innovation Cities is possible, an appropriate comparison group should be chosen for a causal inference on the innovation impact of relocation. Following Greenstone et al. (2010), this paper adopts a winner-loser comparison strategy, where comparison groups are either runner-ups or all other candidate municipalities.

Incorporating these two approaches, Table 1 shows the changes in the number of patent applications by type and region for two sub-sample periods. Columns (1)-(4) show the changes between 2003 and 2011, whereas columns (5)-(8) show the changes between 2011 and 2019. To begin with the the Innovation Cities in the fifth row, columns (1) and (5) show that total innovation in Innovation Cities is increasing faster between 2011 and 2019 than between 2003 and 2011. Given the slowdown of innovation in other regions, this acceleration is remarkable.

In addition, columns (2) and (6) reveal this acceleration of innovation in Innovation Cities is importantly driven by the solo work of relocated agencies that moved from the Northwest region. Between 2011 and 2019, solo work decreases in the Northwest region and increase in Innovation Cities, which accounts for 81.7% of the difference in total innovation between two sub-periods in Innovation Cities..[19] By construction, the increase in solo works is not observed for runner-up municipalities and other candidate municipalities.

[18]Dating back to Marshall's The Principles of Economics, the "knowledge in the air" has been hypothesized as an important channel through which new ideas are generated: *if one man starts a new idea, it is taken up by others and combined with suggestions of their own; and thus it becomes the source of further new ideas.*

[19]The contribution of solo work is computed by $\frac{(1767)}{4025-1862} \times 100$.

Table 1: Patenting changes by the relevance with relocated agencies

	Total (03-11) (1)	Solo (03-11) (2)	Co-work (03-11) (3)	Indep (03-11) (4)	Total (11-19) (5)	Solo (11-19) (6)	Co-work (11-19) (7)	Indep (11-19) (8)
Total	35,088	1,114	204	33,770	19,209	416	226	18,567
Northwest	21,320	1,114	186	20,020	10,740	-1,351	-140	12,231
Non-northwest	13,768	0	18	13,750	8,469	1,767	366	6,336
Candidates	11,590	0	3	11,587	6,212	1,767	372	4,073
Innovation Cities	1,862	0	-4	1,866	4,025	1,767	360	1,898
Runner-ups	775	0	5	770	389	0	3	386

Note: Northwest region includes Seoul, Incheon, Kyunggi-do, Chungcheongnam-do, and Daejeon. Changes in the number of patent applications between 2003 and 2011, and 2011 and 2019 are reported in columns (1)-(4) and (5)-(8), respectively. The types of patent used are total, solo work by relocated agencies, co-work by relocated agencies and local agencies, and local independent work for columns (1) and (5), (2) and (6), (3) and (7), and (4) and (8), respectively.

Moreover, columns (3) and (7) show that co-work between relocated and local agencies increases in Innovation Cities, which shows a direct spillover effect of relocation. The increase in co-work in Innovation Cities between 2011 and 2019 is significantly larger compared to the first sub-period, which is a stark contrast to much weaker increase in other regions.

Finally, it is not clear whether there exists indirect spillover effects beyond co-work since columns (4) and (8) show that the change in local independent innovation is only marginally larger in the second sub-period than the first sub-period. However, this requires a further investigation since the change in local independent work is actually smaller in runner-up municipalities and other candidate municipalities in the second sub-period. In other words, it is possible that local independent innovation in Innovation Cities does not decelerate due to the indirect spillover effects from the relocation unlike the comparison groups.

Now, since this paper utilizes other candidate municipalities that were not selected as Innovation Cities as control groups, it is important to examine whether they are comparable to Innovation Cities. Table 2 shows how different Innovation Cities are from other candidate municipalities and the rest municipalities between 2003 and 2011 before the relocation started.[20] Columns (1)-(4) show the mean of municipality characteristics for Innovation Cities, runner-up municipalities (Runner-up), all non-winner candidate municipalities including runner-up municipalities (Candidate), and all non-winner non-Northwest municipalities (Full). Columns (5)-(7) show the t statistics for the difference between Innovation Cities and municipalities in each comparison group.

Table 2: Municipality characteristics

	Winner (1)	Runner-up (2)	Candidate (3)	Full (4)	t stat (1)-(2) (5)	t stat (1)-(3) (6)	t stat (1)-(4) (7)
No. of municipalities	14	4	72	122			
Patent application	173.4	174.1	161.9	147.8	-0.0	0.4	0.9
change (%)	14.1	17.0	23.5	23.1	-0.6	-1.5	-1.5
Population (thousands)	237.9	206.3	156.3	141	1.1	4.94***	6.44***
change (%)	-0.1	-0.1	-0.5	-0.6	0.02	1.80*	2.45**
Employment (thousands)	63.4	63.5	48.8	44.5	-0.02	2.60***	3.72***
change (%)	3.1	1.9	4.3	3.6	0.58	-0.53	-0.26
MFG share	20.5	12.6	21.2	18	2.49**	-0.49	1.70*
change (%p)	0.2	-0.1	0.6	0.4	0.39	-0.56	-0.38
Busi. services share	16.5	16.8	12.8	13.4	-0.28	7.38***	4.73***
change (%p)	0.2	0.2	0.2	0.3	0.17	-0.07	-0.57
No. of Universities	1.4	0.8	0.6	0.5	2.40**	5.97***	7.29***
change (count)	0.03	0	0.01	0	0.76	1.5	1.85*

Note: Columns (1)-(4) show the mean of variables for Innovation Cities, runner-up municipalities, candidate municipalities, other non-northwest municipalities between 2003 and 2011, respectively. For the number of universities, the average between 2006 and 2011 is used. Columns (5)-(7) show the t-statistics for the mean difference between municipalities. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

The runner-up municipalities seem to be the closest comparison group even though they are statistically different from Innovation Cities for variables including the employment share of manufacturing and the number of universities. However, importantly, the number of patent applications in runner-up municipalities is not statistically different from Innovation Cities, and the difference is economically negligible. The growth rate of patent applications in Innovation Cities is also not statistically distinguishable from runner-up municipalities,

[20]For the number of universities, the average between 2006 and 2011 is used due to the data coverage.

indicating no pre-existing differences in trend. Interestingly, patent applications in runner-up municipalities show faster (although insignificant) growth between 2003 and 2011. Therefore, if innovation increases in Innovation Cities after the relocation of public agencies compared to runner-up municipalities, this may not be due to the advantages that Innovation Cities already have. Indeed, Appendix 4 shows no pre-existing innovation trend for Innovation Cities when runner-up municipalities are considered as a comparison group.

Regarding patent applications, the candidate municipalities and all non-Northwest municipalities are not statistically different from Innovation Cities, both in terms of level and growth. The average number of patent applications is smaller in these municipalities, but its average growth rate is larger than Innovation Cities, although they are not statistically significant. Again, if innovation increases in Innovation Cities compared to these municipalities, this may not be due to the pre-existing advantages or trends. In this regard, despite they are not as close as the runner-up municipalities, and they are statistically different in other variables including population and employment, the candidate municipalities and non-Northwest municipalities are also used to check the robustness of the empirical results.

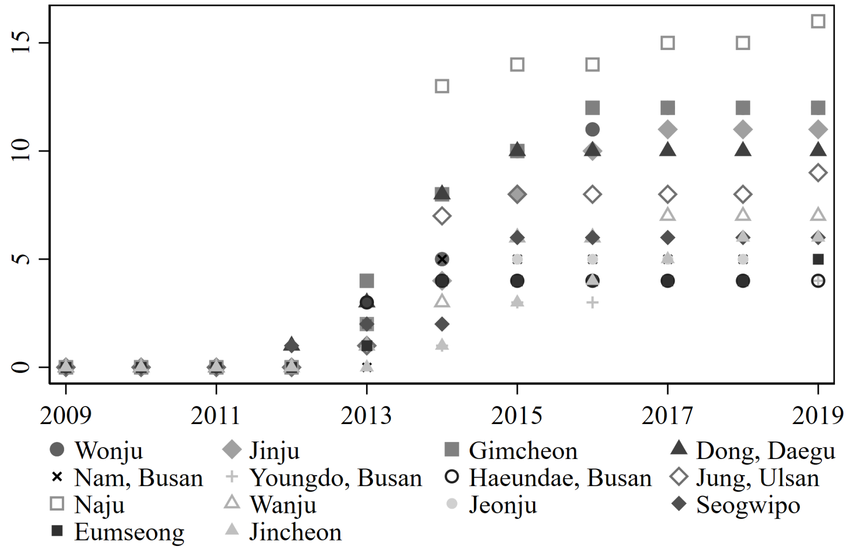
5 Empirical Strategies

5.1 Baseline

A time-varying continuous measure of shock is developed in this paper since commonly used Difference-in-Differences (DiD) method and its variants may not perfectly capture the impact of relocation on local innovation for two reasons.

First, since multiple public agencies relocated to Innovation Cities at different time, the timing and the intensity of treatment are heterogeneous both within and across Innovation Cities. It took seven years to complete the relocation, and the speed of relocation was different for each Innovation City as is described in Figure 3, which shows the accumulated number of public agencies relocated to each Innovation City by year. This staggered and gradual relocation should be taken into account for a precise analysis.

Figure 3: Gradual relocation of public agencies



Note: The vertical axis shows the accumulated number of public agencies relocated.

Second, each relocated agency has different innovation capacity and could have heterogeneous impact on Innovation Cities. To mitigate this concern and to capture the intensity of relocation more precisely, a time-varying continuous measure of shock is developed using how many patents each relocated agency applied for prior to the relocation. More specifically, the innovation capacity of each relocated agency is proxied by the three-year average number of patent applications before the relocation.[21] Then, this innovation capacity of relocated agencies is accumulated at each Innovation City as relocation occurs. Formally, for municipality m, the relocated innovation capacity by year t is

$$RI_{mt} = \mathbf{1}(\, m \in Innovaion\ City\,) \sum_{j} (avgInn_j \times location_{mjt}) \tag{1}$$

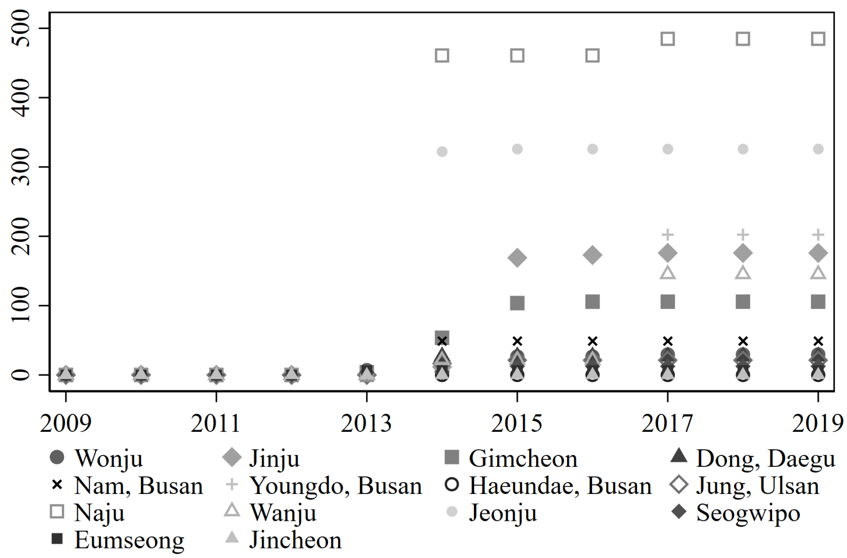
where $\mathbf{1}()$ is a binary indicator that is one if m is Innovation City. Therefore, RI_{mt} is zero for all municipalities that are not Innovation Cities. $avgInn_j$ is relocated agency j's time-

[21] If an agency relocates at time t, then the innovation capacity of the agency is proxied by the average number of patent applications in $t-1$, $t-2$, and $t-3$. Appendix 3 shows that relocated agencies are heterogeneous in their innovation capacity.

invariant innovation capacity proxied by the average number of patent applications within three years before the relocation. A dummy variable $location_{mjt}$ indicates whether relocated agency j is in municipality m in year t. By aggregating up the interaction terms, this measure captures the accumulated innovation capacity relocated to each Innovation City.[22]

Figure 4 visualizes the accumulated innovation capacity relocated to each Innovation City by year. By combining both heterogeneous innovation capacity of relocated agencies and the timing of relocation, this measure shows that the intensity of shock varies significantly across Innovation Cities over time.

Figure 4: Time-varying treatment intensity



Note: The vertical axis shows the accumulated innovation capacity relocated.

Equipped with this time-varying continuous treatment intensity variable, the following equation is estimated:

$$y_{mt} = \beta RI_{mt} + \delta_m + \mu_t + X'_{mt}\Lambda + \varepsilon_{mt}, \tag{2}$$

where the municipality-level y_{mt} includes the total number of patent applications, solo work

[22] For instance, suppose agency A with 100 average patent applications and agency B with 50 average patent applications moved to Innovation City m in 2013 and 2014, respectively. Then, $RI_{mt} = 0$ for $t < 2013$ since relocation does not happen yet. Then, as agency A relocated in 2013, relocated innovation capacity changes to $RI_{m,2013} = 100$, and it increases to $RI_{m,2014} = 150$ as agency B moves in 2014. Since there is no further relocation after 2014, $RI_{mt} = 150$ for $t > 2014$.

by relocated agencies, co-work by relocated agencies and local agencies, and independent work by local agencies. Since RI_{mt} is the number of accumulated innovation capacity relocated to Innovation Cities, β captures how many patents of each type are generated in Innovation Cities when one potential patent relocates to Innovation Cities, which is interpreted as a local innovation multiplier. Municipality fixed effects δ_m, year fixed effects μ_t, and municipality-level controls X_{mt} including population, employment (in logarithms), the employment share of manufacturing, the employment share of business service, and the number universities are controlled. Standard errors ε_{mt} are clustered at the province level.

Moreover, to investigate the heterogeneous impact across Innovation Cities, the following equation is estimated:

$$y_{mt} = \beta_1 RI_{mt} + \beta_2 RI_{mt} \times Innovative_m + \delta_m + \mu_t + X'_{mt}\Lambda + \varepsilon_{mt}, \tag{3}$$

where $Innovative_m$ is a binary indicator identifying municipalities whose number of patent applications between 2003 and 2011 is within the top 30th percentile.[23] Therefore, β_1 indicates the local innovation multiplier of relatively less innovative municipalities pre-relocation, and β_2 captures different responses by municipalities that were active in innovation.

5.2 By Technological Similarity

If knowledge spillovers from relocated agencies exist, the spillover effect is expected to be stronger in the area where relocated agencies' expertise lie in. To investigate this, technology information documented in patent filing is utilized to construct a panel covering local innovation by technology field. More specifically, one of eight technology fields is designated to each patent based on the first technology field that patent applicants report upon application based on the International Patent Classification (IPC) system.[24] Then, these patents

[23] Northwest region is excluded when computing the innovation percentile of municipalities.

[24] Eight technology fields are human necessities (A); performing operations and transporting (B); chemistry and metallurgy (C); textiles and paper (D); fixed constructions (E); mechanical engineering, lighting, heating, weapons, and blasting (F); physics (G); and electricity (H).

are aggregated at the municipality-field level over time as a measure of local innovation by field. Finally, to distinguish the relocated innovation capacity in the same field from other fields, two variables are constructed for municipality m in technology field f at time t:

$$RI_{mft} = \mathbf{1}(\,m \in Innovaion\ City\,) \sum_{j} (avgInn_{fj} \times location_{mjt})\,, \tag{4}$$

$$RIrest_{mft} = \mathbf{1}(\,m \in Innovaion\ City\,) \sum_{j} \sum_{f' \neq f} (avgInn_{f'j} \times location_{mjt})\,, \tag{5}$$

where $avgInn_{fj}$ is the three-year average number of patents in field f that relocated agency j applied prior to relocation.[25] Therefore, RI_{mft} captures the innovation capacity in field f relocated to municipality m by year t, and $RIrest_{mft}$ indicates the innovation capacity in all other fields relocated to m by t.[26] These continuous treatment intensity variables measure not only the innovation capacity of relocated agencies and the timing of relocation, but also heterogeneous technology fields in which relocated agencies innovate. Equipped with these shock variables, the following equation is estimated:

$$y_{mft} = \beta_1 RI_{mft} + \beta_2 RIrest_{mft} + \delta_m + \mu_t + X'_{mt}\Lambda + \varepsilon_{mft}, \tag{6}$$

where the municipality-field level dependent variable includes total number of patent applications, solo work, co-work, and local independent work. Now, the coefficients of interests are β_1 and β_2, which capture the within-field effect and the cross-field effect, respectively. Since knowledge spillovers are expected to be stronger within the same technology field, β_1 is expected to be larger than β_2. Fixed effects and control variables are included, and standard errors are clustered at the province level consistent with the baseline analysis.

In addition, heterogeneous responses across Innovation Cities are examined by estimat-

[25] Since relocated agency's innovation can be decomposed into the sum of innovation in each field, adding up $avgInn_{fj}$ of all f recovers $avgInn_j$ in equation (1). Formally, we have $\sum_f avgInn_{fj} = avgInn_j$.

[26] For all municipality m, the accumulated innovation capacity relocated to the municipality can be decomposed into that in field f and in other fields. That is, $RI_{mft} + RIrest_{mft} = RI_{mt}$ for any f.

ing the following equation:

$$y_{mft} = \beta_1 RI_{mft} + \beta_2 RI_{mft} \times Innovative_m + \beta_3 RIrest_{mft} + \beta_4 RIrest_{mft} \times Innovative_m + \delta_m + \mu_t + X'_{mt}\Lambda + \varepsilon_{mft}, \quad (7)$$

where a binary variable $Innovative_m$ indicates municipalities whose number of patent applications before relocation started is within the top 30th percentile as in the baseline analysis. The coefficients of interest are β_1, β_2, β_3, and β_4, which capture the heterogeneous within-field impact and the cross-field impact across Innovation Cities.

5.3 Beyond Innovation Cities

Not only local agencies within Innovation Cities but also in other municipalities close to Innovation Cities may enjoy increased interactions with relocated agencies, which implies the possibility of spillovers beyond Innovation Cities. However, since spillovers are more likely to happen when there exist frequent interactions, the spillover effects are expected to be decreasing in distance, if they exist. Therefore, to explore the spatial scope of spillover effects beyond Innovation Cities, the physical distance between each municipality and Innovation Cities is used in addition to the technological similarity. More specifically, to examine how municipality m's innovation in technology field f in year t is affected by the relocation of public agencies to its neighborhood within $d\,km$, the magnitude of innovation capacity in the same field relocated to each municipality's neighborhood is measured as follows:

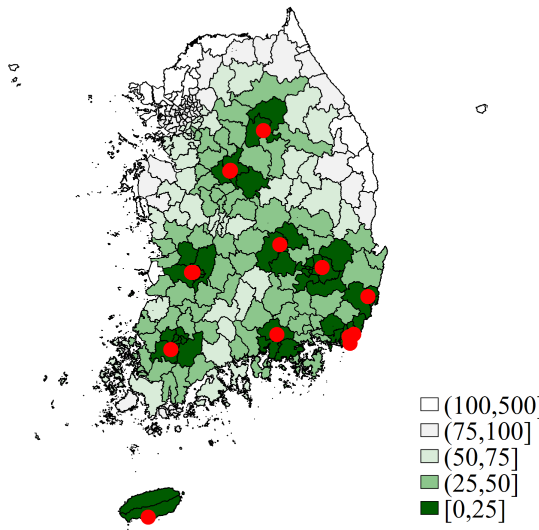
$$RINeighbor^{d}_{mft} = \sum_i RI_{ift} \times \mathbf{1}(\,distance_{im} < d\,), \quad (8)$$

where $\mathbf{1}(\,distance_{im} < d\,)$ is one when the centroid of municipality m is less than $d\,km$ away from Innovation City i.[27] Therefore, if a public agency relocates to Innovation City i, RI_{ift} increases by its innovation capacity for each f, and $RIneighbor^{d}_{mft}$ increases by the same

[27] The location of Innovation City is defined as the centroid of relocated agencies.

amount for all municipalities within $d\,km$ from i. To be realistic, exposures to multiple Innovation Cities within $d\,km$ are allowed and added up. Figure 5 shows the distance from each municipality to the nearest Innovation City.

Figure 5: Distance to the nearest Innovation City



Analogously, the magnitude of innovation capacity in other technology fields relocated to m's neighborhood is measured as:

$$RIrestNeighbor^{d}_{mft} = \sum_{i} RIrest_{ift} \times \mathbf{1}(\,distance_{im} < d\,), \tag{9}$$

which uses $RIrest_{ift}$ instead of RI_{ift}. Equipped with these measures, the following equation is estimated similar to Faggio (2019):

$$y_{mft} = \sum_{d} \beta_{1d} RINeighbor^{d}_{mft} + \sum_{d} \beta_{2d} RIrestNeighbor^{d}_{mft} + \delta_m + \mu_t + X'_{mt}\Lambda + \varepsilon_{mft}, \tag{10}$$

where dependent variable y_{mft} includes the total number of patent applications, co-works, and local independent works in municipality m in technology field f in year t.[28] All non-Northwest municipalities excluding Innovation Cities are used in the estimation to focus on the spillover effects beyond Innovation Cities, not limiting to candidate municipalities or

[28]Solo work, which is always zero in this analysis, is not used as a dependent variable.

runner-up municipalities, and $d = 25, 50, 75, 100$ are used to examine the spatial scope of the spillover effects. Municipality fixed effects, year fixed effects, municipality-level control variables are included, and standard errors are clustered at the province level. The within-field and cross-field spillover effects beyond Innovation Cities are captured by β_{1d} and β_{2d}, respectively. If knowledge spillovers attenuate in distance, β_{1d} and β_{2d} will decrease in d.

6 Results

6.1 Baseline

Table 3: Impact of the relocation of public agencies on local innovation

	Full		Candidate		Runner-up	
	(1)	(2)	(3)	(4)	(5)	(6)
Total	1.457***	1.368***	1.272***	1.261***	1.351***	1.314***
	(0.236)	(0.185)	(0.239)	(0.210)	(0.238)	(0.184)
Solo	0.973***	0.970***	0.972***	0.966***	0.975***	0.972***
	(0.035)	(0.033)	(0.035)	(0.033)	(0.028)	(0.027)
Co-work	0.136***	0.134***	0.135***	0.133***	0.134***	0.134***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.013)
Independent	0.349	0.263	0.165	0.161	0.242	0.208
	(0.265)	(0.214)	(0.270)	(0.237)	(0.253)	(0.194)
# universities		✓		✓		✓
N	2397	1974	1462	1204	306	252

Note: This table shows the regression results of (2) using different control groups for each type of innovation. Columns (1)-(2) use all other non-Northwest municipalities, whereas columns (3)-(4) and (5)-(6) use all non-winning candidate municipalities and runner-up municipalities as control groups, respectively. All columns include population and employment in logarithm, employment share of manufacturing, and employment share of business services as control variables. In addition, columns (2), (4), and (6) include the number of universities as an additional control variable. All models include municipality fixed effects and year fixed effects. Standard errors in parenthesis are clustered by province. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 3 shows the results of estimating main equation (2) using different types of innovation and different control groups. Classifying patents with the relevance with relocated agencies, each row reports the estimated β using the total number of patent applications, solo work by relocated agencies, co-work with relocated agencies, and independent work by local agencies as dependent variables. Control groups used in columns (1)-(2) are all other municipalities in the non-Northwest region, whereas they are restricted to candidate municipalities in columns (3)-(4) and to runner-up municipalities in columns (5)-(6), respectively. Columns (2), (4), and (6) include the number of universities in each municipality as an additional control variable, which shortens the sample period from 2003-2019 to 2006-2019.

Note that coefficients associated with the total number of patent applications in the first row is the sum of other coefficients in the same column. It is because the total number of patent applications can be decomposed into the number of solo works, co-works, and local independent works. Note further that the estimated results are qualitatively not sensitive to comparison groups. In contrast, the DiD results in Appendix 4 are sensitive to the control group emphasizing the importance of comparison groups and the precise measurement of treatment intensity. Four more things need to be highlighted.

First, regardless of the choice of comparison groups and control variables, all coefficients related to total innovation are positive and significant at the one percent levels, which implies that local innovation in Innovation Cities increases as a result of the relocation of public agencies. More importantly, coefficients associated with total innovation or the local innovation multiplier is larger than one. When one potential innovation is relocated to Innovation Cities, Innovation Cities produce more than one innovation, although some of them are not statistically different from one considering the standard errors.

Second, due to the mechanical relocation, solo work increases in Innovation Cities as expected. All solo work coefficients are positive and significant at the one percent level. However, these coefficients are between 0.966 and 0.975, which are smaller than one. Relocated agencies apply for fewer number of patents after relocation when solo work is considered. This is an intuitive result since public agencies were physically relocated from their optimal location to Innovation Cities. Indeed, Byun (2016) reports that 6,999 out of 32,944 employees voluntarily quit from public agencies those relocated between 2013 and 2015, and relocated agencies experience difficulty in attracting talents after relocation.[29] This could

[29] High skilled workers with better job opportunities may have stayed in Seoul looking for better amenities.

have decreased the innovation of public agencies after relocation.

Third, collaboration between relocated agencies and local agencies increases in Innovation Cities, which clearly indicates the existence of direct spillover effects. Coefficients associated with co-work are at least as large as 0.133 and all significant at the one percent level. As public agencies relocate to Innovation Cities, and the interaction between public agencies and local agencies increases, the number of patents jointly applied by relocated agencies and local agencies increases significantly in Innovation Cities. This increase in co-work offsets the loss of solo works in that the sum of solo work coefficient and co-work coefficient is at least 1.099 and statistically larger than one. Local innovation increases more than relocated potential innovation in spite of the decrease in solo work by relocated agencies.

Fourth, the indirect spillover effects captured by the increased independent innovation by local agencies are all positive but not statistically significant. It is possible that the relocation of public agencies to Innovation Cities improves the innovation environments or increases the "knowledge in the air", which therefore increases local agencies' independent innovation. In order for a regional development policy to succeed in boosting innovation, and therefore accelerating regional growth, whether local agencies increase innovation and start to generate second-round spillover effects should be important. However, at least on average, the empirical evidence does not support that this channel is in effect.

Quantitatively speaking, the coefficients in column (5), the preferred specification, imply that local innovation in Innovation Cities increases by 29.4% per year compared to runner-up municipalities after the first relocation, where 21.2%p of the increase is due to the solo work, 2.9%p of the increase is due to the co-work, and 5.3%p is due to the insignificant increase in local independent work.[30] This magnitude of increase in innovation is around half of what Andrews (2023) finds: U.S. college counties have 62% more patents per year than runner-up counties after the establishment of colleges. Although it is not straightforward to clarify the

[30]Considering the average RI between 2012 and 2019 is 72.18, the innovation multiplier for total local innovation is 1.351, and the average local innovation in runner-up municipalities is 331.2, the contribution of relocation to the change in total local innovation is computed as $\frac{72.18 \times 1.351}{331.2} \times 100$. Coefficients of solo work, co-work, and local independent work are used analogously to compute their contribution.

source of this difference, it is not too surprising to see smaller increase in Innovation Cities since universities produce highly educated workforce unlike relocated public agencies, which could boost local innovation through other channels.

Table 4: Heterogeneous impact of the relocation of public agencies on local innovation

	Full		Candidate		Runner-up	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Total						
RI	1.134***	1.096***	0.926***	0.958***	1.010***	1.040***
	(0.122)	(0.113)	(0.100)	(0.087)	(0.129)	(0.101)
$RI \times Innovative$	0.936***	0.779***	0.975***	0.844***	0.903***	0.717***
	(0.094)	(0.104)	(0.110)	(0.086)	(0.172)	(0.135)
Panel B. Solo						
RI	0.959***	0.955***	0.957***	0.950***	0.956***	0.948***
	(0.041)	(0.040)	(0.040)	(0.038)	(0.026)	(0.025)
$RI \times Innovative$	0.041	0.045	0.041	0.047	0.049	0.061
	(0.078)	(0.078)	(0.078)	(0.076)	(0.066)	(0.062)
Panel C. Co-work						
RI	0.135***	0.133***	0.134***	0.132***	0.135***	0.135***
	(0.013)	(0.013)	(0.013)	(0.012)	(0.010)	(0.009)
$RI \times Innovative$	0.003	0.004	0.002	0.004	-0.003	-0.002
	(0.035)	(0.035)	(0.035)	(0.034)	(0.029)	(0.029)
Panel D. Independent						
RI	0.040	0.009	-0.166*	-0.123	-0.081	-0.043
	(0.107)	(0.089)	(0.089)	(0.071)	(0.096)	(0.070)
$RI \times Innovative$	0.893***	0.730***	0.931***	0.793***	0.857***	0.658***
	(0.160)	(0.153)	(0.187)	(0.141)	(0.220)	(0.173)
# universities		✓		✓		✓
N	2397	1974	1462	1204	306	252

Note: This table shows the regression results of (3) using different control groups for each type of innovation. Coefficients of the treatment intensity variable RI_{mt} and its interaction term with $Innovative_m$ are reported for each dependent variable. Columns (1)-(2) use all other non-Northwest municipalities, whereas columns (3)-(4) and (5)-(6) use all non-winning candidate municipalities and runner-up municipalities as control groups, respectively. All columns include population and employment in logarithm, employment share of manufacturing, and employment share of business services as control variables. In addition, columns (2), (4), and (6) include the number of universities as an additional control variable. All models include municipality fixed effects and year fixed effects. Standard errors in parenthesis are clustered by province. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

The empirical results considering the heterogeneous innovation response of regions in Table 4, which report the coefficients of treatment intensity variable RI_{mt} and its interaction with $Innovative_m$, show a stark contrast with to the previous results. First of all, as shown in Panel A, the number of patent applications increases in Innovation Cities, but the increase is much stronger in municipalities that were already active in innovation before the relocation. All coefficients of interaction term are positive and significant at the one percent level, and the magnitude is economically meaningful. The local innovation multipliers of relatively less innovative municipalities lie between 0.926 and 1.114, whereas those of more innovative municipalities range between 1.757 and 2.07.[31] The impact of relocation on local innovation is between 1.69 to 2.04 times stronger in relatively more innovative municipalities.

Second, more importantly, this heterogeneous response is almost entirely driven by how local agencies change their independent innovation after relocation as shown in Panel D. The RI coefficients are negative or statistically not different from zero, meaning that local independent innovation does not increase in relatively less innovative municipalities after public agencies relocate. However, coefficients of the interaction term are all positive and significant at the one percent level, showing that local independent innovation increases in more innovative municipalities as a result of the relocation of public agencies. Considering the coefficients of the interaction term in Panel A, this stronger response in local independent innovation explains between 91.8 and 95.4 percent of the stronger response in total innovation in more innovative municipalities.

Third, as is shown in Panel B and Panel C, more innovative municipalities do not show any statistically different response in solo work and co-work to the relocation of public agencies. The coefficients of the interaction term in both panels are insignificant unlike the precisely estimated coefficients of treatment intensity variable.

Combining all these and considering the relocated innovation capacity, the coefficients in column (5) imply that local innovation in Innovation Cities that were relatively less innovative increases by 29.5% per year compared to runner-up municipalities after the first relocation. This increase is mostly driven by solo work, which explains 28.0%p of the increase,

[31] These are computed as the sum of RI coefficient and the interaction coefficient.

and only minor fraction of the increase is due to the spillovers. Co-work explains only 3.9%p of the increase, and the contribution of local independent work is even negative (-2.4%p) although it is not statistically significant.

In contrast, local innovation in Innovation Cities that were relatively more innovative increases by 31.0% per year compared to runner-up municipalities after the first relocation. Although this magnitude of increase seems similar to the increase in less innovative Innovation Cities, two things are noteworthy. First, this small difference is due to the weaker shock that more innovative municipalities experienced instead of less pronounced response. The average relocated innovation capacity between 2012 and 2019 is 96.9 and 53.7 for those were less innovative and more innovative, respectively. Although more innovative Innovation Cities received weaker shocks, the increase in innovation in these municipalities turns out to be larger due to their stronger response. Second, importantly, a meaningful part of this increase, specifically 2.1%p from co-work and 12.6%p from local independent work, arises from spillover effects on top of the mechanical contribution of 16.4%p from the solo work.[32]

These results have a clear and important policy implication. Policymakers should consider the existing innovative capacity of a region when planning regional development policies to accelerate regional innovation, the engine of growth. Given the importance of knowledge spillovers for innovation, these results are not too surprising. If agglomeration fosters innovation through increased interaction, then an exogenous surge in innovation capacity would yield a stronger upswing in regions with more innovators to interact and with well-established network that relocated agencies can participate in. Moreover, since local agencies innovate and generate spillovers by themselves, the second-round spillover effects are expected to be stronger in regions that were already active in innovation as well. This is exactly what is observed in the empirical evidence, and this is what policymakers should take into account.

[32] The average RI between 2012 and 2019 is 96.9 and 53.7, whereas the innovation multiplier for total local innovation is 1.04 and 1.757 for less and more innovative Innovation Cities, respectively. Given the average local innovation in runner-up municipalities is 331.2, the change in total local innovation that can be contributed to the relocation is computed as $\frac{96.9 \times 1.04}{331.2} \times 100$ and $\frac{53.7 \times 1.757}{331.2} \times 100$ for less and more innovative Innovation Cities, respectively. Coefficients of solo work, co-work, and local independent work are used analogously to compute their contribution.

Table 5: Impact of the relocation on local innovation by the size of shock

	Full		Candidate		Runner-up	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Total						
RI	1.587***	1.391***	1.041***	1.103***	1.004**	1.021***
	(0.267)	(0.179)	(0.295)	(0.198)	(0.350)	(0.264)
$RI \times Big$	-0.136	-0.016	0.271	0.188	0.385	0.324
	(0.422)	(0.335)	(0.486)	(0.378)	(0.405)	(0.277)
Panel B. Solo						
RI	1.048***	1.038***	1.044***	1.023***	1.006***	0.963***
	(0.156)	(0.158)	(0.164)	(0.174)	(0.203)	(0.209)
$RI \times Big$	-0.078	-0.070	-0.074	-0.057	-0.030	0.013
	(0.152)	(0.155)	(0.159)	(0.171)	(0.198)	(0.202)
Panel C. Co-work						
RI	0.197***	0.194***	0.195***	0.189***	0.184**	0.174**
	(0.046)	(0.048)	(0.048)	(0.052)	(0.060)	(0.063)
$RI \times Big$	-0.069	-0.067	-0.067	-0.063	-0.054	-0.042
	(0.044)	(0.047)	(0.046)	(0.052)	(0.059)	(0.063)
Panel D. Independent						
RI	0.342	0.159	-0.198	-0.110	-0.186	-0.115
	(0.298)	(0.253)	(0.226)	(0.166)	(0.256)	(0.194)
$RI \times Big$	0.011	0.121	0.413	0.308	0.468	0.353
	(0.413)	(0.350)	(0.423)	(0.336)	(0.324)	(0.197)
# universities		✓		✓		✓
N	2397	1974	1462	1204	306	252

Note: This table shows the regression results of (3) using a binary variable for municipalities under larger shocks. Coefficients of the treatment intensity variable RI_{mt} and their interaction with Big_m are reported for each dependent variable. Columns (1)-(2) use all other non-Northwest municipalities, whereas columns (3)-(4) and (5)-(6) use all non-winning candidate municipalities and runner-up municipalities as control groups, respectively. All columns include population and employment in logarithm, employment share of manufacturing, and employment share of business services as control variables. In addition, columns (2), (4), and (6) include the number of universities as an additional control variable. All models include municipality fixed effects and year fixed effects. Standard errors in parenthesis are clustered by province. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Now, given that agglomeration plays an important role, policymakers may wonder whether policies that are strong enough initiate a virtuous cycle of innovation and spillovers. Indeed, economics literature has studied a "big push" strategy, which relies on the idea that economic development exhibit threshold effects (Rosenstein-Rodan, 1943; Murphy et al., 1989; Azariadis and Stachurski, 2005; Kline and Moretti, 2014a). To examine whether Innovation Cities facing larger shocks generate greater spillover effects, equation (7) is estimated replacing $Innovative_m$ with a binary variable Big_m, which identifies municipalities where cumulative innovation capacity relocated by 2019 is within the top 30th percentile. Table 5 reports the results.

In stark contrast to the previous results, the size of shock does not generate statistically significant difference in innovation response. Although the magnitude is slightly different, the RI coefficients are positive and significant at least at the five percent level for total innovation, solo work, and co-work similar to the previous results. However, interaction coefficients are not significant in all panels regardless of the comparison group and control variables, and their signs are not consistent with the big-push hypothesis in some specifications.

Previous results in Table 4 suggest that relocating public agencies to regions with a better innovation outcome exhibit stronger effects mostly due to the increase in local independent innovation, which is important for establishing a self-reinforcing innovation cluster. However, this type of heterogeneous response is not observed when the size of shock is larger. This could be because even larger shocks are not sufficient to make a difference, because fewer interactions between local agencies result in weaker second-round spillover effects, or because it is more difficult for relocated agencies to facilitate interactions within the locality than participating in the existing network. However, regardless of the reasons, at least in terms of knowledge spillovers and innovation within locality, initial environments turn out to be more important than the size of shock. Therefore, in planning place-based policies, including the relocation of public agencies, opening of universities, or supporting start-ups in specific regions, policymakers should take the innovation environments of regions into consideration.

6.2 By Technological Similarity

Table 6 shows the estimated coefficients for RI_{mft} and $RIrest_{mft}$ from regressing equation (6), which show the impact of relocated innovation capacity on local innovation by technological similarity. Same as the baseline results in Table 3, each column uses different control groups and includes different control variables. Panel A reports the estimated coefficients using the total number of patent applications by field as a dependent variable, whereas Panel B, C, and D use solo work, co-work, and local independent work by field as dependent variables, respectively. Four things are noticeable.

Table 6: Impact of the relocation on local innovation by technological similarity

	Full		Candidate		Runner-up	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Total						
RI	1.469***	1.457***	1.445***	1.444***	1.455***	1.450***
	(0.160)	(0.155)	(0.162)	(0.159)	(0.160)	(0.154)
$RIrest$	0.000	-0.011	-0.023*	-0.024**	-0.013	-0.018*
	(0.014)	(0.008)	(0.012)	(0.009)	(0.015)	(0.009)
Panel B. Solo						
RI	0.990***	0.989***	0.989***	0.989***	0.989***	0.989***
	(0.062)	(0.061)	(0.062)	(0.061)	(0.061)	(0.060)
$RIrest$	-0.001	-0.002	-0.001	-0.002	-0.001	-0.002
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)
Panel C. Co-work						
RI	0.125***	0.125***	0.125***	0.125***	0.125***	0.125***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
$RIrest$	0.002	0.001	0.002	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Panel D. Independent						
RI	0.354	0.343	0.331	0.330	0.341	0.336
	(0.232)	(0.226)	(0.234)	(0.230)	(0.230)	(0.224)
$RIrest$	-0.000	-0.011	-0.023**	-0.024**	-0.013	-0.018
	(0.012)	(0.009)	(0.009)	(0.007)	(0.014)	(0.012)
# universities		✓		✓		✓
N	19176	15792	11696	9632	2448	2016

Note: This table shows the regression results of (6) using different control groups for each type of innovation. Coefficients of the treatment intensity variable RI_{mft} and $RIrest_{mft}$ are reported for each dependent variable. Columns (1)-(2) use all other non-Northwest municipalities, whereas columns (3)-(4) and (5)-(6) use all non-winning candidate municipalities and runner-up municipalities as control groups, respectively. All columns include population and employment in logarithm, employment share of manufacturing, and employment share of business services as control variables. In addition, columns (2), (4), and (6) include the number of universities as an additional control variable. All models include municipality fixed effects and year fixed effects. Standard errors in parenthesis are clustered by province. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

First of all, regardless of comparison groups and control variables, the RI coefficients in Panel A, which show the impact of relocated innovation capacity on the total number of patent applications within the same technology field, are all positive and significant at the one percent level. As a result of the relocation of innovation capacity embedded in public agencies, local innovation in the same technology field increases. In contrast, the $RIrest$ coefficients in Panel A, which capture knowledge spillovers across technology fields, are not significant or even negative and significant. Within-field effects turn out to be more important than cross-field effects in the increase in local innovation.

Quantitatively speaking, coefficients in column (1) mean that relocating one potential innovation generates 1.469 patents in the same field and no change in other fields. Coefficients in other columns can be interpreted analogously. As is expected, the within-field coefficients ranging between 1.444 and 1.469 are much larger than cross-field coefficients between 0.000 to 0.024 (in absolute value), showing that the relocation of innovation capacity affects local innovation in the same technology field rather than in different technology fields.[33]

Second, the results in Panel B are consistent with the baseline results in Table 3 and the previous results in Panel A at the same time. Solo work increases due to the mechanical relocation, and this increase is dominated by the increase in the same technology field. The within-field coefficients are all positive and significant at the one percent level. However, the cross-field coefficients are not statistically distinguishable from zero, implying that relocated agencies continue innovating in the technology field that they have expertise in. Again, the RI coefficients are smaller than one, although statistically not different from one.

Third, Panel C shows that the relocation of public agencies boosts collaboration with local agencies in the same technology field, whereas it does not accelerate collaboration across fields. All RI coefficients are positive and significant at the one percent level, and all $RIrest$ coefficients are not distinguishable from zero. More specifically, coefficients in column (1) means that relocating public agencies with one potential innovation generates

[33]Due to this importance of the within-field effect, the RI coefficients in Panel A are larger than those in Table 3. The baseline results do not distinguish the within-field effect and the cross-field effect.

0.125 patent that is joint applied with local agencies in the same field, whereas it does not generate statistically meaningful change in the other fields. Coefficients in other columns can be interpreted similarly for different comparison groups and different control variables. Consistent with the baseline results, direct spillover effects through collaboration are observed, and the within-field spillovers dominate the effects.

Finally, Panel D reports that the relocation of public agencies does not have statistically significant effects of local independent innovation when spillovers within-field and cross-fields are separately considered consistent with the baseline results. All within-field coefficients are positive but not significant. Although cross-field coefficients are significant in columns (3) and (4), they are not significant when the closest comparison group is considered in columns (5) and (6), and their magnitude is relatively small. Again, on average, this empirical evidence does not support the indirect spillover through the "knowledge in the air" channel.

In sum, the previous story continues to hold in that local innovation increases in Innovation Cities, which is driven by a mechanical increase in solo work and an increase in co-work. The role of local independent innovation is muted from a statistical perspective. At the same time, by shedding light on technological similarity between local innovation and relocated innovation capacity, it is found that this rise in local innovation is largely driven by the same technology field that relocated agencies have innovated in. These results highlight the existence and importance of knowledge spillover channel how relocation of public agencies affects local innovation. As expected, local innovation responds more strongly in the same technology field where relocated agencies are actively engaged probably because it is easier for innovators in the similar field to collaborate or learn from each other. If other factors that coincide with the relocation, such as improvement in infrastructure and amenities, better access to venture capital, increase in local population are more important drivers, then the change in local innovation should not be limited to the fields in which relocated agencies innovate. However, this is not what is observed from the empirical evidence.

Table 7: Heterogeneous impact of relocation on local innovation by technological similarity

	Full		Candidate		Runner-up	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Total						
RI	1.251***	1.246***	1.225***	1.228***	1.235***	1.239***
	(0.020)	(0.020)	(0.016)	(0.017)	(0.022)	(0.021)
$RI \times Innovative$	0.495***	0.475***	0.500***	0.484***	0.490***	0.467***
	(0.045)	(0.045)	(0.049)	(0.045)	(0.053)	(0.048)
$RIrest$	-0.015	-0.020	-0.041**	-0.037***	-0.031*	-0.027**
	(0.015)	(0.014)	(0.013)	(0.011)	(0.015)	(0.011)
$RIrest \times Innovative$	0.064***	0.044***	0.069***	0.052***	0.059**	0.036**
	(0.011)	(0.012)	(0.010)	(0.009)	(0.018)	(0.015)
Panel B. Solo						
RI	1.033***	1.032***	1.033***	1.032***	1.032***	1.031***
	(0.053)	(0.053)	(0.053)	(0.053)	(0.052)	(0.051)
$RI \times Innovative$	-0.091	-0.090	-0.091	-0.090	-0.090	-0.089
	(0.055)	(0.055)	(0.055)	(0.055)	(0.053)	(0.052)
$RIrest$	-0.009***	-0.010***	-0.010***	-0.011***	-0.010**	-0.011*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
$RIrest \times Innovative$	0.019**	0.020**	0.019**	0.020**	0.020**	0.021**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Panel C. Co-work						
RI	0.133***	0.133***	0.133***	0.133***	0.133***	0.133***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
$RI \times Innovative$	-0.017	-0.016	-0.017	-0.016	-0.017	-0.017
	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.012)
$RIrest$	0.000	0.000	0.000	-0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$RIrest \times Innovative$	0.003	0.003	0.003	0.003	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Panel D. Independent						
RI	0.085	0.081	0.059	0.064	0.070	0.074
	(0.061)	(0.058)	(0.059)	(0.060)	(0.053)	(0.056)
$RI \times Innovative$	0.602***	0.582***	0.607***	0.590***	0.598***	0.573***
	(0.093)	(0.090)	(0.095)	(0.090)	(0.093)	(0.090)
$RIrest$	-0.006	-0.010	-0.032*	-0.027*	-0.021	-0.016
	(0.016)	(0.015)	(0.015)	(0.013)	(0.018)	(0.015)
$RIrest \times Innovative$	0.042**	0.022	0.047**	0.030*	0.038	0.013
	(0.014)	(0.015)	(0.018)	(0.013)	(0.024)	(0.019)
# universities		✓		✓		✓
N	19176	15792	11696	9632	2448	2016

Note: This table shows the regression results of (7) using different control groups for each type of innovation. Coefficients of the treatment intensity variable RI_{mft}, $RIrest_{mft}$, and their interaction with Big_m are reported for each dependent variable. Columns (1)-(2) use all other non-Northwest municipalities, whereas columns (3)-(4) and (5)-(6) use all non-winning candidate municipalities and runner-up municipalities as control groups, respectively. All columns include population and employment in logarithm, employment share of manufacturing, and employment share of business services as control variables. In addition, columns (2), (4), and (6) include the number of universities as an additional control variable. All models include municipality fixed effects and year fixed effects. Standard errors in parenthesis are clustered by province. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Now, regional heterogeneity is considered similar to the baseline analysis in addition to the technological fields. Table 7 reports the estimated coefficients for equation (7). To begin with the within-field effects, it is not surprising to observe the positive and significant coefficients for RI and $RI \times Innovative$ in Panel A, given the stronger responses in municipalities that were already active in innovation before the shock. As potential innovation relocates to Innovation Cities, local innovation in the same technology field increases, and the increase is more pronounced if innovation was already active there.

Confirming the previous results, this heterogeneity is entirely driven by local independent innovation within the same field as shown in Panel D. The $RI \times Innovative$ coefficients, which show how local independent innovation in more innovative municipalities responds differently, are positive and significant at the one percent level unlike the negative but insignificant coefficients in Panel B and C. Indeed, the $RI \times Innovative$ coefficients in Panel A and Panel D imply that more than 100% of the stronger response of total local innovation in more innovative municipalities is explained by local independent innovation.

Turning to the cross-field effects, Panel A shows that the relocated innovation capacity has an impact on local innovation in other fields unlike Table 6. The $RIrest$ coefficients are significant in columns (3)-(6), and the $RIrest \times Innovative$ coefficients are all significant at least at the five percent level. However, despite their statistical significance, these results do not contrast to the previous results, which emphasize the innovation in the same technology field. Instead, they reinforce the previous implications in two ways.

First, compared to the within-field coefficients, the size of cross-field coefficients are smaller by a magnitude of order. Coefficients in column (1) of Panel A show that as one potential innovation relocates to Innovation Cities, local patent applications in the same field increases by 1.251 in less innovative municipalities and by 1.746 in more innovative municipalities. In contrast, local patent in other fields decreases by 0.015 in less innovative municipalities and increases by 0.049 in more innovative municipalities. The within-field effects are economically more important.

Second, as is reported in Panel B, C, and D, statistically significant cross-field impact found in Panel A is mostly due to the change in solo work. All $RIrest$ and $RIrest \times Innovative$ coefficients are significant in Panel B, whereas they are not significant or not consistently significant in Panel C and D. Although the significant coefficients in Panel B reveal how relocated public agencies adjust their innovation activities depending on the local innovation experience, there is little direct linkage between this adjustment and the knowledge spillovers effect, which this paper focuses on.[34]

Finally, echoing the baseline results, Table 8 shows that the magnitude of shock does not result in different response even when technology fields are taken into account. The RI coefficients are significant at the one percent level for Panel A, B, and C, indicating local innovation in Innovation Cities increases due to the increase in solo work and co-work in the same field. However, the $RI \times Big$ coefficients are not significant for all Panels in all columns implying that regions under a larger shock do not respond more strongly to the relocation of public agencies in terms of the innovation in the same technology field.

Turning to the cross-field effects, the $RIrest$ and $RIrest \times Big$ coefficients are not significant in Panel A, implying that cross-field effects are not statistically important in local innovation response to the relocation of public agencies, and larger shocks do not make a difference. Although some of the cross-field coefficients in Panel B, C, and D are weakly significant, they are not consistently significant, and some of these coefficients are even negative in contrast to the big-push hypothesis. Lastly, the magnitude of these coefficients are relatively small similar to those in Table 7, which means the cross-field impact is economically not important as within-field impact.

All these results considering technological similarity and regional heterogeneity confirm the policy implication drawn from the baseline results. Policymakers should take the prior experience of innovation in locality into account since it affects magnitude knowledge spillovers.

[34] Solo work in other fields could have changed due to the interaction with local innovators. However, in that case, co-work and local independent work could have been affected too, which is not observed.

Table 8: Impact of the relocation on local innovation by the size of shock and by technology

	Full		Candidate		Runner-up	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Total						
RI	1.354***	1.329***	1.286***	1.293***	1.280***	1.283***
	(0.079)	(0.071)	(0.081)	(0.072)	(0.088)	(0.085)
$RI \times Big$	0.129	0.144	0.180	0.169	0.194	0.187
	(0.190)	(0.180)	(0.197)	(0.184)	(0.181)	(0.164)
$RIrest$	0.034	0.010	-0.034	-0.026	-0.039	-0.036
	(0.033)	(0.023)	(0.036)	(0.026)	(0.040)	(0.028)
$RIrest \times Big$	-0.039	-0.023	0.012	0.002	0.027	0.019
	(0.037)	(0.027)	(0.045)	(0.033)	(0.039)	(0.029)
Panel B. Solo						
RI	0.949***	0.948***	0.949***	0.946***	0.943***	0.938***
	(0.118)	(0.118)	(0.119)	(0.120)	(0.122)	(0.122)
$RI \times Big$	0.045	0.046	0.046	0.048	0.052	0.057
	(0.115)	(0.116)	(0.117)	(0.118)	(0.121)	(0.121)
$RIrest$	0.015**	0.014*	0.015*	0.012	0.009	0.004
	(0.006)	(0.006)	(0.007)	(0.009)	(0.014)	(0.015)
$RIrest \times Big$	-0.018**	-0.017*	-0.018*	-0.016	-0.012	-0.006
	(0.008)	(0.008)	(0.009)	(0.009)	(0.013)	(0.013)
Panel C. Co-work						
RI	0.143***	0.143***	0.143***	0.143***	0.142***	0.140***
	(0.031)	(0.031)	(0.031)	(0.032)	(0.032)	(0.033)
$RI \times Big$	-0.021	-0.020	-0.020	-0.020	-0.019	-0.017
	(0.028)	(0.028)	(0.028)	(0.029)	(0.030)	(0.030)
$RIrest$	0.008***	0.007**	0.008**	0.007*	0.006	0.005
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
$RIrest \times Big$	-0.007**	-0.007**	-0.007**	-0.006	-0.005	-0.004
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Panel D. Independent						
RI	0.261	0.238	0.194	0.205	0.195	0.204
	(0.145)	(0.146)	(0.130)	(0.135)	(0.136)	(0.142)
$RI \times Big$	0.104	0.118	0.154	0.141	0.161	0.147
	(0.230)	(0.225)	(0.229)	(0.223)	(0.216)	(0.205)
$RIrest$	0.011	-0.012	-0.056	-0.045*	-0.054	-0.045*
	(0.034)	(0.026)	(0.033)	(0.023)	(0.034)	(0.020)
$RIrest \times Big$	-0.013	0.001	0.037	0.024	0.043	0.029
	(0.033)	(0.024)	(0.037)	(0.025)	(0.029)	(0.020)
# universities		✓		✓		✓
N	19176	15792	11696	9632	2448	2016

Note: This table shows the regression results of (7) using a binary variable for municipalities under larger shocks. Coefficients of the treatment intensity variable RI_{mft}, $RIrest_{mft}$, and their interaction with Big_m are reported for each dependent variable. Columns (1)-(2) use all other non-Northwest municipalities, whereas columns (3)-(4) and (5)-(6) use all non-winning candidate municipalities and runner-up municipalities as control groups, respectively. All columns include population and employment in logarithm, employment share of manufacturing, and employment share of business services as control variables. In addition, columns (2), (4), and (6) include the number of universities as an additional control variable. All models include municipality fixed effects and year fixed effects. Standard errors in parenthesis are clustered by province. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

6.3 Beyond Innovation Cities

Investigating the knowledge spillover effects further, Table 9 shows the estimated within-field coefficients for equation (10), which informs the spatial scope of spillovers beyond Innovation Cities. Cross-field coefficients are not reported, but they are mostly insignificant, inconsistent, and small in magnitude, emphasizing the importance of within-field effects again. Columns (2)-(5) include the number of universities as an additional control variable, and each column includes a different combination of municipality fixed effects, year fixed effects, province-year fixed effects, technology fixed effects, and technology-year fixed effects to consider additional unobservable heterogeneity and time trend. Each panel shows the results using different dependent variables, and each row shows the spillover effects by distance.

Panel A shows that knowledge spillovers beyond Innovation Cities exist, but they are limited to close regions. Coefficients related to $25km$ are positive and significant at least at the five percent level for all specifications, whereas coefficients for farther distance are not distinguishable from zero. Knowledge spillovers are sharply attenuating in distance, which is similarly found in the literature. For instance, Arzaghi and Henderson (2008) show that the benefits networking through agglomeration disappear by $750m$ in advertising agency in Manhattan, and Andersson et al. (2009) show that half of the gains from investment in universities are concentrated within $5-8km$. Also, Rosenthal and Strange (2001) show that knowledge spillovers affect agglomeration only at the postal code level.

Quantitatively, the $25km$ coefficients in Panel A imply that relocating one potential innovation to Innovation Cities generates 0.146 to 0.166 patent application in neighboring municipalities within $25km$. Interestingly, this effect is dominantly driven by the change in local independent innovation. Unlike the insignificant coefficients in Panel B, all $25km$ coefficients in Panel C are positive and significant, and their value is almost identical to those in Panel A. The speed of attenuation in distance seems to be faster for collaboration than indirect spillovers via the "knowledge in the air", which is intuitive since collaboration often requires networking, frequent visits, and shared office or equipment.

Table 9: Spatial scope of knowledge spillovers

	(1)	(2)	(3)	(4)	(5)
Panel A. Total					
$0-25km$	0.150**	0.156**	0.166***	0.146**	0.143**
	(0.055)	(0.050)	(0.052)	(0.053)	(0.055)
$0-50km$	-0.042	-0.045	-0.042	-0.040	-0.038
	(0.062)	(0.059)	(0.057)	(0.051)	(0.048)
$0-75km$	0.016	0.010	0.012	0.014	0.015
	(0.050)	(0.048)	(0.049)	(0.047)	(0.049)
$0-100km$	0.051	0.058	0.055	0.002	-0.010
	(0.033)	(0.035)	(0.035)	(0.027)	(0.027)
Panel B. Co-work					
$0-25km$	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$0-50km$	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$0-75km$	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$0-100km$	0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel C. Independent					
$0-25km$	0.150**	0.156**	0.165***	0.146**	0.143**
	(0.054)	(0.049)	(0.052)	(0.052)	(0.054)
$0-50km$	-0.042	-0.045	-0.041	-0.039	-0.038
	(0.061)	(0.059)	(0.057)	(0.050)	(0.048)
$0-75km$	0.015	0.010	0.012	0.014	0.014
	(0.050)	(0.048)	(0.048)	(0.047)	(0.048)
$0-100km$	0.051	0.057	0.055	0.002	-0.010
	(0.033)	(0.035)	(0.035)	(0.027)	(0.027)
# universities		✓	✓	✓	✓
Municipality FE	✓	✓	✓	✓	✓
Year FE	✓	✓		✓	
Province-year FE			✓		
Technology FE				✓	
Technology-year FE					✓
N	17272	14224	14224	14224	14224

Note: This table reports the estimated within-field coefficients for equation (10) to show the spatial scope of knowledge spillovers for non-Northwest municipalities. All columns include population and employment in logarithm, employment share of manufacturing, and employment share of business services as control variables. In addition, columns (2)-(6) include the number of universities as an additional control variable. Standard errors in parenthesis are clustered by province. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

The evidence of the localized knowledge spillovers within the same field provides insight on the formation of innovation clusters, characterized by the geographic concentration of firms, research institutes, and innovation activities within a specific industry or technology field. In equilibrium, those who stay in the concentrated area should be those who benefit from agglomeration the most since spatial concentration involves higher costs. Given this, the spatial concentration of innovation is intuitive because knowledge spillovers diminish rapidly in physical distance, and those who enjoy spillovers from others' innovation the most will stay in the cluster. Moreover, since knowledge spillovers are stronger in the same technology field, it is not surprising that we observe innovation clusters specializing in specific industries or technology fields.

7 Conclusion

This paper examines the knowledge spillover effects facilitated by a quasi-experimental South Korean Innovation City project, which relocated public agencies from Seoul metropolitan area to provincial regions. The Innovation City project has several distinct features that enable to estimate the causal impact of the relocation on local innovation consequences. First, since public agencies are relocated to Innovation Cities, the pre-relocation information about the relocated agencies can be used. This allows to develop a continuous treatment intensity variable using the innovation history of relocated agencies to incorporate the heterogeneity of relocated agencies precisely. Second, since the universe of Korean patent data is available, local innovation in Innovation Cities can be classified by the relevance with relocated agencies. By doing so, the mechanical impact of relocation is distinguished from its spillover effects, and how responsive each type of innovation is to the relocation can be computed, which is represented by the innovation multiplier. Third, detailed information in the patent data also allows to investigate the differential impact of relocation by technological similarity and geographical proximity. Since knowledge spillovers are expected to be stronger within the same technology, and in geographically proximate regions, this information is used to refine the transmission of knowledge more precisely. Finally, since information about other candidate municipalities is available, a winner-loser comparison can be conducted to estimate the causal impact of the Innovation City project.

The empirical evidence shows that the relocation of public agencies increases innovation in Innovation Cities not only by the solo work of relocated agencies, which is more mechanical, but also by the co-work between local agencies and relocated agencies, which reveals increased interactions and spillovers. More importantly, considering the heterogeneous innovation experience between regions, I find that the increase in local innovation is stronger in regions already active in innovation, and this more pronounced response is almost entirely driven by local independent innovation. Furthermore, these spillover effects are stronger within the same technology field and geographically limited to very close regions, implying that knowledge spillovers attenuate in economic distance. These results clearly indicate where regional development policies should target to stimulate regional innovation and therefore growth efficiently. At the same time, these results inform economists why we observe innovation clusters around the world, where technologically specialized innovation is spatially concentrated.

Even though this paper shows the innovation consequences of the Innovation City project, the results should be interpreted with caution for three reasons. First, the aggregate impact is not evaluated. Since introducing public agencies increases innovation in Innovation Cities, it is possible that municipalities where public agencies departed from may have experienced a decrease in innovation. However, due to the lack of appropriate comparison groups, this possibility is not investigated. Therefore, whether this spatial reallocation of innovation capacity generates net gains or net losses is not answered in this paper. Second, it might be too early to evaluate the Innovation City project since the relocation of public agencies was complete in 2019, which is the last year of the sample period. It may take longer to form networks, disperse knowledge, and invent new knowledge. In addition, it is possible that educational attainment and migration pattern change due to the decent job opportunities in Innovation Cities, which can generate longer term impact on local innovation. Third, this paper only focuses on innovation, and no other outcome variables are explored. Policy implications derived from the current study do not consider other possible goals of place-based policies. Evaluating the Innovation City project, even at the local level, requires analyzing its impact on many other factors. All this requires future research.

References

Abbate, J. (2000): *Inventing the Internet*, MIT press.

Adams, J. D. (2002): "Comparative Localization of Academic and Industrial Spillovers," *Journal of Economic Geography*, 2, 253–278.

Aghion, P., A. Dechezleprêtre, D. Hemous, R. Martin, and J. Van Reenen (2016): "Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry," *Journal of Political Economy*, 124, 1–51.

Agrawal, A., A. Galasso, and A. Oettl (2017): "Roads and Innovation," *The Review of Economics and Statistics*, 99, 417–434.

Andersson, R., J. M. Quigley, and M. Wilhelmsson (2009): "Urbanization, Productivity, and Innovation: Evidence from Investment in Higher Education," *Journal of Urban Economics*, 66, 2–15.

Andrews, M. J. (2023): "How do Institutions of Higher Education Affect Local Invention? Evidence from the Establishment of US Colleges," *American Economic Journal: Economic Policy*, 15, 1–41.

Arzaghi, M. and J. V. Henderson (2008): "Networking off Madison Avenue," *The Review of Economic Studies*, 75, 1011–1038.

Autor, D., D. Dorn, G. H. Hanson, G. Pisano, and P. Shu (2020): "Foreign Competition and Domestic Innovation: Evidence from US Patents," *American Economic Review: Insights*, 2, 357–374.

Azariadis, C. and J. Stachurski (2005): "Poverty Traps," *Handbook of Economic Growth*, 1, 295–384.

Azoulay, P., J. S. Graff Zivin, and J. Wang (2010): "Superstar Extinction," *The Quarterly Journal of Economics*, 125, 549–589.

Becker, B. (2015): "Public R&D Policies and Private R&D Investment: A Survey of the Empirical Evidence," *Journal of Economic Surveys*, 29, 917–942.

Becker, S. O., S. Heblich, and D. M. Sturm (2021): "The Impact of Public Employment: Evidence from Bonn," *Journal of Urban Economics*, 122, 103291.

Belenzon, S. and M. Schankerman (2013): "Spreading the Word: Geography, Policy, and Knowledge Spillovers," *The Review of Economics and Statistics*, 95, 884–903.

Billings, S. B. and E. B. Johnson (2016): "Agglomeration within an Urban Area," *Journal of Urban Economics*, 91, 13–25.

Bloom, N., M. Draca, and J. Van Reenen (2016): "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity," *The Review of Economic Studies*, 83, 87–117.

Briant, A., M. Lafourcade, and B. Schmutz (2015): "Can Tax Breaks Beat Geography? Lessons from the French Enterprise Zone Experience," *American Economic Journal: Economic Policy*, 7, 88–124.

Busso, M., J. Gregory, and P. Kline (2013): "Assessing the Incidence and Efficiency of a Prominent Place Based Policy," *American Economic Review*, 103, 897–947.

Bustos, P. (2011): "Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms," *American Economic Review*, 101, 304–340.

Buzard, K., G. A. Carlino, R. M. Hunt, J. K. Carr, and T. E. Smith (2020): "Localized Knowledge Spillovers: Evidence from the Spatial Clustering of R&D Labs and Patent Citations," *Regional Science and Urban Economics*, 81, 103490.

Byun, J. (2016): "Evaluation of the Public Sector Relocation Program," National Assembly Budget Office Policy Evaluation 16-05.

Calel, R. (2020): "Adopt or Innovate: Understanding Technological Responses to Cap-and-trade," *American Economic Journal: Economic Policy*, 12, 170–201.

Clemens, M. A., E. G. Lewis, and H. M. Postel (2018): "Immigration Restrictions as Active Labor Market Policy: Evidence from the Mexican Bracero Exclusion," *American Economic Review*, 108, 1468–1487.

Cowan, R. and N. Zinovyeva (2013): "University Effects on Regional Innovation," *Research Policy*, 42, 788–800.

Daniels, P. W. (1985): *Service Industries: a Geographical Appraisal*, Routledge.

David, P. A., B. H. Hall, and A. A. Toole (2000): "Is Public R&D a Complement or Substitute for Private R&D? A Review of the Econometric Evidence," *Research Policy*, 29, 497–529.

Ellison, G., E. L. Glaeser, and W. R. Kerr (2010): "What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns," *American Economic Review*, 100, 1195–1213.

Faggio, G. (2019): "Relocation of public sector workers: Evaluating a place-based Policy," *Journal of Urban Economics*, 111, 53–75.

Faggio, G. and H. Overman (2014): "The Effect of Public Sector Employment on Local Labour Markets," *Journal of Urban Economics*, 79, 91–107.

Gilson, R. J. (1999): "The Legal Infrastructure of High Technology Industrial Districts: Silicon Valley, Route 128, and Covenants Not to Compete," *NYU Law Review*, 74, 575.

Giroud, X. (2013): "Proximity and Investment: Evidence from Plant-level Data," *The Quarterly Journal of Economics*, 128, 861–915.

Givord, P., R. Rathelot, and P. Sillard (2013): "Place-based Tax Exemptions and Displacement Effects: An Evaluation of the Zones Franches Urbaines Program," *Regional Science and Urban Economics*, 43, 151–163.

Glaeser, E. and J. Gottlieb (2008): "The Economics of Place-making Policies," *Brookings Papers on Economic Activity*.

Greenstone, M., R. Hornbeck, and E. Moretti (2010): "Identifying Agglomeration Spillovers: Evidence from Winners and Losers of Large Plant Openings," *Journal of Political Economy*, 118, 536–598.

Gross, D. P. and B. N. Sampat (2023): "America, Jump-started: World War II R&D and the Takeoff of the US Innovation System," *American Economic Review*, 113, 3323–3356.

Hall, B. and J. Van Reenen (2000): "How Effective Are Fiscal Incentives for R&D? A Review of the Evidence," *Research Policy*, 29, 449–469.

Hanley, D., J. Li, and M. Wu (2022): "High-speed Railways and Collaborative Innovation," *Regional Science and Urban Economics*, 93, 103717.

Hunt, J. and M. Gauthier-Loiselle (2010): "How Much Does Immigration Boost Innovation?" *American Economic Journal: Macroeconomics*, 2, 31–56.

Jaffe, A. B. (1986): "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value," *The American Economic Review*, 76, 984–1001.

——— (1989): "Characterizing the "Technological Position" of Firms, with Application to Quantifying Technological Opportunity and Research Spillovers," *Research Policy*, 18, 87–97.

Jaffe, A. B., M. S. Fogarty, and B. A. Banks (1998): "Evidence from Patents and Patent Citations on the Impact of NASA and Other Federal Labs on Commercial Innovation," *The Journal of Industrial Economics*, 46, 183–205.

Jaffe, A. B. and K. Palmer (1997): "Environmental Regulation and Innovation: a Panel Data Study," *Review of Economics and Statistics*, 79, 610–619.

Jaffe, A. B., M. Trajtenberg, and R. Henderson (1993): "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations," *The Quarterly Journal of Economics*, 108, 577–598.

Jeon, M. S. and J. S. Lee (2021): "Is Public Agency Relocation Effective to Achieve Decentralization? Evaluating its Effects on Regional Employment," *Journal of Urban Affairs*.

Jofre-Monseny, J., J. I. Silva, and J. Vázquez-Grenno (2020): "Local Labor Market Effects of Public Employment," *Regional Science and Urban Economics*, 82, 103406.

Kang, M. (2023): "Export Competition and Innovation," *Available at SSRN 4610397*.

Kantor, S. and A. Whalley (2014): "Knowledge Spillovers from Research Universities: Evidence from Endowment Value Shocks," *Review of Economics and Statistics*, 96, 171–188.

——— (2019): "Research Proximity and Productivity: Long-term Evidence from Agriculture," *Journal of Political Economy*, 127, 819–854.

Kerr, W. R. and W. F. Lincoln (2010): "The Supply Side of Innovation: H-1B Visa Reforms and US Ethnic Invention," *Journal of Labor Economics*, 28, 473–508.

Kline, P. and E. Moretti (2014a): "Local economic development, agglomeration economies, and the big push: 100 years of evidence from the Tennessee Valley Authority," *The Quarterly Journal of Economics*, 129, 275–331.

——— (2014b): "People, Places, and Public Policy: Some Simple Welfare Economics of Local Economic Development Programs," *Annual Review of Economics*, 6, 629–662.

Kneller, R. and E. Manderson (2012): "Environmental Regulations and Innovation Activity in UK Manufacturing Industries," *Resource and Energy Economics*, 34, 211–235.

Koster, H. R. A. and J. van Ommeren (2019): "Place-based Policies and the Housing Market," *The Review of Economics and Statistics*, 101, 400–414.

Lee, H., C. Ko, and W. Kim (2023): "Local Employment Multiplier: Evidence from Relocation of public-sector entities in South Korea," *CESifo Working Paper*, No. 10870.

Lu, Y., J. Wang, and L. Zhu (2019): "Place-based Policies, Creation, and Agglomeration Economies: Evidence from China's Economic Zone Program," *American Economic Journal: Economic Policy*, 11, 325–360.

Marshall, J., D. Bradley, C. Hodgson, N. Alderman, and R. Richardson (2005): "Relocation, Relocation, Relocation: Assessing the Case for Public Sector Dispersal," *Regional Studies*, 39, 767–787.

Marshall, J. N. (2007): "Public Sector Relocation Policies in the UK and Ireland," *European Planning Studies*, 15, 645–666.

Marx, M., D. Strumsky, and L. Fleming (2009): "Mobility, Skills, and the Michigan Non-compete Experiment," *Management Science*, 55, 875–889.

Matray, A. (2021): "The Local Innovation Spillovers of Listed Firms," *Journal of Financial Economics*, 141, 395–412.

Moretti, E. (2010): "Local Multipliers," *American Economic Review*, 100, 373–77.

Moretti, E. and P. Thulin (2013): "Local Multipliers and Human Capital in the United States and Sweden," *Industrial and Corporate Change*, 22, 339–362.

Moser, P., A. Voena, and F. Waldinger (2014): "German Jewish émigrés and US Invention," *American Economic Review*, 104, 3222–3255.

Murata, Y., R. Nakajima, R. Okamoto, and R. Tamura (2014): "Localized Knowledge Spillovers and Patent Citations: A Distance-based Approach," *Review of Economics and Statistics*, 96, 967–985.

Murphy, K. M., A. Shleifer, and R. W. Vishny (1989): "Industrialization and the Big Push," *Journal of Political Economy*, 97, 1003–1026.

Neumark, D. and J. Kolko (2010): "Do Enterprise Zones Create Jobs? Evidence from California's Enterprise Zone Program," *Journal of Urban Economics*, 68, 1–19.

Neumark, D. and H. Simpson (2015): "Place-based Policies," in *Handbook of Regional and Urban Economics*, Elsevier, vol. 5, 1197–1287.

Pfister, C., M. Koomen, D. Harhoff, and U. Backes-Gellner (2021): "Regional Innovation Effects of Applied Research Institutions," *Research Policy*, 50, 104197.

Rosenstein-Rodan, P. N. (1943): “Problems of Industrialisation of Eastern and South-eastern Europe,” *The Economic Journal*, 53, 202–211.

Rosenthal, S. S. and W. C. Strange (2001): “The Determinants of Agglomeration,” *Journal of Urban Economics*, 50, 191–229.

——— (2003): “Geography, Industrial Organization, and Agglomeration,” *Review of Economics and Statistics*, 85, 377–393.

Rossi-Hansberg, E., P.-D. Sarte, and R. Owens III (2010): “Housing Externalities,” *Journal of Political Economy*, 118, 485–535.

Schweiger, H., A. Stepanov, and P. Zacchia (2022): “The Long-run Effects of R&D Place-based Policies: Evidence from Russian Science Cities,” *American Economic Journal: Economic Policy*, 14, 322–351.

Seo, S. and D. W. Kwak (2024): “The Impact of the Innovation City Project on the Local Economy: Evidence from Korean Innovation City Project from 2012 to 2014,” *Journal of Asian Economics*, 90, 101677.

Takamura, Y. and K. Tone (2003): “A Comparative Site Evaluation Study for Relocating Japanese Government Agencies out of Tokyo,” *Socio-Economic Planning Sciences*, 37, 85–102.

Trajtenberg, M., R. Henderson, and A. Jaffe (1997): “University Versus Corporate Patents: A Window on the Basicness of Invention,” *Economics of Innovation and New Technology*, 5, 19–50.

Waldinger, F. (2012): “Peer Effects in Science: Evidence from the Dismissal of Scientists in Nazi Germany,” *The Review of Economic Studies*, 79, 838–861.

Wang, J. (2013): “The Economic Impact of Special Economic Zones: Evidence from Chinese Municipalities,” *Journal of Development Economics*, 101, 133–147.

Wang, J. and S. Cai (2020): “The Construction of High-speed Railway and Urban Innovation capacity: Based on the Perspective of Knowledge Spillover,” *China Economic Review*, 63, 101539.

Xue, J. (2022): "Human Capital Reallocation and Agglomeration of Innovation: Evidence from Technological Breakthroughs," *Job Market Paper*.

Appendix 1 Innovation City Selection Guideline

Table A1: Innovation City site selection rubric

Criteria	Weight
Possibility of Development as Innovation Hub	
Proximity to transportation	20
Suitability as innovation hub	20
Availability of infrastructure and convenient facilities of the existing cities	20
Need for City Development	
Readiness and economic effect of city development	15
Environmentally-friendly development sites	10
Possibility of Shared Growth within Region	
Balanced development within region	10
Ways to share achievements of innovation city	10
Local government's support	5

Source: Ministry of land, infrastructure, and transportation.

Appendix 2 Sector Classification

Table A2: Sector classification

Sector	KSIC 8th	KSIC 9th	KSIC 10th
Agriculture	A, B, C	A, B	A, B
Manufacturing	D except 22100	C	C except 34000
Construction	F	F	F
Personal services	G, H, O, P, Q, R, S	G, I, P, Q, R, S	G, I, P, Q, R, S plus 34000
Business services	I, J, K, L, M, plus 22100	H, J, K, L, M, N	H, J, K, L, M, N
Other	E, N, T	D, E, O, T, U	D, E, O, T, U

Note: Publication (22100) is reclassified as business service since it is classified as manufacturing in the 8th revision. Reparation of machinery is reclassified as personal service since it is classified as manufacturing in the 10th revision.

Appendix 3 Innovation Capacity of Relocated Agencies

Table A3 shows that relocated public agencies are substantially heterogeneous in their innovation capacity. The most innovative public agency applied for more than 351 patents on average before relocation, whereas the tenth innovative public agency applied for only 35 patents. Reflecting this heterogeneity, the average innovation capacity of relocated agencies is 24.2, and its standard deviation is 51.0.

Table A3: Top 10 Innovative Relocated Public Agencies

Name	Innovation Capacity	Location	Year of Relocation
Korea Electric Power Corporation	351.3	Naju	2014
Rural Development Administration	321.3	Jeonju	2014
Korea Institute of Ocean Science and Technology	198.3	Youngdo, Busan	2017
Korea Institute of Ceramic Engineering	137.0	Jinju	2015
Korea Food Research Institute	124.0	Wanju	2017
Korea Southern Power	53.0	Naju	2014
KEPCO Plant Service and Engineering	49.0	Naju	2014
Animal and Plant Quarantine Agency	41.3	Gimcheon	2015
KEPCO Knowledge, Database, and Network	41.0	Naju	2014
Korea Expressway	35.3	Gimcheon	2014

Note: Innovation capacity of relocated agencies is proxied by their 3-year average number of patent applications before the year of relocation.

Appendix 4 Additional Empirical Results

Appendix 4.1 Difference-in-Differences

The DiD method is used to estimate whether the relocation of public agencies affects innovation and whether it has knowledge spillover effects in Innovation Cities. More formally, the following equation is estimated:

$$y_{mt} = \beta InnCity_m \times Treat_{mt} + \delta_m + \mu_t + X'_{mt}\Lambda + \varepsilon_{mt}, \tag{A1}$$

where $InnCity_m$ is an indicator of municipalities that public agencies relocate to, and $Treat_{mt}$ is one from the year when the first relocation happens for each municipality. Similar to the baseline regression, fixed effects and municipality-level controls are included in the regression. Standard errors ε_{mt} are clustered at the province level.

Table A4: Impact of the relocation of public agencies (DiD)

	Full		Candidate		Runner-up	
	(1)	(2)	(3)	(4)	(5)	(6)
Total	141.088**	128.116**	72.608	82.973	68.418	96.949
	(59.382)	(54.116)	(50.462)	(47.507)	(89.022)	(81.555)
Solo	74.683**	74.216**	70.890**	70.644**	62.944	75.182
	(31.187)	(30.287)	(29.371)	(27.900)	(38.677)	(41.475)
Co-work	11.202**	11.061**	10.534**	10.245**	8.043	9.234
	(4.321)	(4.030)	(4.044)	(3.738)	(4.671)	(5.251)
Independent	55.204	42.839	-8.816	2.084	-2.569	12.533
	(42.227)	(36.645)	(38.495)	(32.818)	(55.704)	(46.314)
# universities		✓		✓		✓
N	2397	1974	1462	1204	306	252

Note: This table shows the regression results of (A1) using different control groups for each type of innovation. Columns (1)-(2) use all other non-Northwest municipalities, whereas columns (3)-(4) and (5)-(6) use all non-winning candidate municipalities and runner-up municipalities as control groups, respectively. All columns include population and employment in logarithm, employment share of manufacturing, and employment share of business services as control variables. In addition, columns (2), (4), and (6) include the number of universities as an additional control variable. All models include municipality fixed effects and year fixed effects. Standard errors in parenthesis are clustered by province. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table A4 shows the estimation results of (A1) using different types of innovation and different control groups. The results are sensitive to the control group emphasizing the importance of choosing an appropriate comparison group. When all non-Northwest municipalities are considered, columns (1) and (2) show that the relocation of public agencies increases total innovation, solo work by relocated agencies, and the co-work of relocated agencies and local agencies in Innovation Cities significantly, whereas the impact of relocation on local independent work is statistically not distinguishable from zero. Coefficients in column (1) show that as a result of the relocation of public agencies, the total number of patent applications in Innovation Cities increases by 141.1 compared to other municipalities on average, and this increase is decomposed into an increase of solo work by 74.7, an increase of co-work by 11.2, and an insignificant increase in local independent work by 55.2.

However, when a comparison group is restricted to other candidate municipalities in columns (3) and (4), the magnitude of coefficients becomes smaller for all types, and the impact on total innovation becomes insignificant. Strikingly, when a control group is restricted to runner-up municipalities in columns (5) and (6), which is the most preferred control group, all coefficients become insignificant indicating no significant impact of relocation on local innovation. These results show that a winner-loser comparison employing a DiD method could be misleading. Unlike the baseline results using the continuous treatment intensity variable, which are qualitatively similar regardless of the control group, imprecise measurement veils the effect of relocation.

Appendix 4.2 Event Study

To investigate the existence of pre-trend and the dynamic response of innovation outcomes, the panel event study framework is employed. Similar to the DiD analysis, the first year of relocation to each Innovation City is designated as the event time, which varies by Innovation Cities from 2012 to 2014. Then, the following equation is estimated:

$$y_{mt} = \alpha + \sum_{j=2}^{J} \beta_j (Lag\, j)_{mt} + \sum_{k=0}^{K} \gamma_k (Lead\, k)_{mt} + \delta_m + \mu_t + X'_{mt}\Lambda + \varepsilon_{mt}, \tag{A2}$$

where the municipality-level innovation variable y_{mt} includes total number of patent applications, solo work, co-work, and local independent innovation as in the main analysis. The coefficients of interest are those of $Lag\, j_{mt}$ and $Lead\, k_{mt}$, which are defined as

$$Lag\, J_{mt} = \mathbf{1}[t \leq Event_m - J] \tag{A3}$$

$$Lag\, j_{mt} = \mathbf{1}[t = Event_m - j] \text{ for } j \in \{2, .., J-1\} \tag{A4}$$

$$Lead\, k_{mt} = \mathbf{1}[t = Event_m + k] \text{ for } j \in \{0, 1, 2, .., K-1\} \tag{A5}$$

$$Lead\, K_{mt} = \mathbf{1}[t \geq Event_m + K] \tag{A6}$$

As is standard, event time dummies are added except one-year prior to the event, which means the coefficients measure the impact relative to the year before the first relocation of public agencies. Municipality fixed effects, year fixed effects, and municipality-level controls are included. Standard errors are clustered at the province level.

Figure A1 shows the estimated coefficients and their 95% confidence intervals. Subfigures in each row show the impact of relocation on different innovation outcome variables, and each column uses different comparison groups. Reassuringly, for all four innovation outcomes, regardless of the comparison group, no statistically significant pre-trend is found. It seems unlikely that the pre-existing trend of innovation drives the baseline results. However, clear and upward trends are found for total innovation, solo work, and co-work in the first three rows, although the estimated coefficients are not statistically significant when the narrowest comparison group is employed in the third column potentially due to the imprecise measurement of shocks. Again, local independent innovation does not show a significant response to the relocation. Echoing the baseline results in the main text, these results imply that local innovation, including solo work and co-work, in Innovation Cities keeps increasing after public agencies relocated.

Figure A1: Dynamic impact of relocation of public agencies