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# AN EMPIRICAL ANALYSIS ON THE KNOWLEDGE SPILLOVERS AND HOUSING PRICE IN YANGTZE RIVER DELTA REGION

**Chaohai Shen**[1]

[1] *Assistant Professor, Faculty of Economics and Management, East China Normal University, China*

## Abstract

The Yangtze River Delta region is one of the economic centers in China and also a hub for innovation activities in the country. The knowledge spillover in the Yangtze River Delta region is not only significant for the region itself but also for the entire nation. At the same time, the high housing prices in the Yangtze River Delta region may have an impact on the knowledge spillover within the region. This study examines the influence of housing prices on knowledge spillover in the major cities of the Yangtze River Delta region based on data from 2001 to 2019. The findings reveal that high housing prices in cities generally have a significant negative effect on knowledge spillover. The magnitude of this effect varies across different measures of knowledge spillover.

## Keywords

Knowledge Spillovers, Housing Price, Innovation, Economic Development, Yangtze River Delta

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## 1. Introduction

Research on knowledge spillovers reflected by R&D spillovers and the geography of innovation and production supports the notion that innovation in cities is not only influenced by local high-tech industry agglomeration and innovation inputs but also by spillover effects from other cities within the urban cluster (Audretsch & Feldman, 1996). Furthermore, studies have indicated that industry agglomeration contributes significantly to innovation, and proximity and spatial dynamics play crucial roles in the evolution of innovation networks (Boschma & Frenken, 2010; Ellison, Glaeser & Kerr, 2010; Glaeser & Kerr, 2009).

In line with these findings, recent studies have explored the effects of industrial agglomeration on regional innovation in China's high-tech industry. Li and Qian (2017) investigated the impact of industrial agglomeration on regional innovation and provided evidence from China's high-tech industry. Their findings highlight the positive effects of industrial agglomeration on regional innovation outcomes.

Additionally, Zhang, Zhou, and Li (2020) examined the relationship between high-tech industry agglomeration, entrepreneurial environment, and regional innovation efficiency in China. Their study revealed the significant influence of high-tech industry agglomeration on regional innovation efficiency, emphasizing the importance of fostering a conducive entrepreneurial environment within the agglomerated regions.

Therefore, taking into account the research on R&D spillovers, the geography of innovation and production, and the effects of industrial agglomeration on regional innovation in China, it becomes evident that promoting high-tech industry agglomeration, enhancing collaboration among cities within urban clusters, and creating a supportive entrepreneurial environment are critical for boosting regional innovation capabilities and achieving coordinated development within urban clusters.

The housing prices could potentially impede this process as they not only elevate the costs for firms but also increase the living expenses for high-skilled workers. Considering the interconnectedness and potential spillover effects across industries, the high housing prices may exacerbate mismatches and further hinder regional innovation. We try to explore how the housing price would impact the knowledge spillover in Yangtze River Delta region.

The Yangtze River Delta region is one of the most prosperous and developed areas in China. According to data, the region's total economic output and per capita GDP have consistently ranked among the top in the country for many years. Taking 2019 as an example, the GDP of the Yangtze River Delta region exceeded 15 trillion yuan, accounting for approximately 24% of the national GDP. In addition, the Yangtze River Delta region is an important hub of scientific and technological innovation in China, with continuous growth in innovation and entrepreneurship activities. Taking Shanghai as an example, according to 2020 data, the city is home to over 200,000 innovative enterprises, attracting a large number of innovative talents and capital investment. The region also boasts numerous prestigious universities, research institutions, and high-tech companies. For instance, Shanghai is home to world-class institutions such as Fudan University, Shanghai Jiao Tong University, and the Chinese Academy of Sciences Shanghai Branch. Moreover, the Yangtze River Delta region is a gathering place for many well-known high-tech companies and innovative enterprises, including Alibaba, Huawei, and Tencent. The concentration of these institutions and companies provides strong impetus and support for technological innovation in the region.

High housing prices affect the distribution and collaboration of businesses. In the Yangtze River Delta region, the elevated housing prices make it challenging for some enterprises to bear the substantial costs associated with office spaces and production facilities. Consequently, some businesses may opt to establish their headquarters or branch offices in cities with lower housing prices instead of cities with high housing costs. As a result, the opportunities for collaboration and knowledge sharing between businesses in high housing price cities and other cities decrease, thereby impacting the extent and quality of knowledge spillovers.

The Yangtze River Delta region has abundant human resources, with a highly skilled workforce and talent pool. Meanwhile, the escalating housing prices in the Yangtze River Delta region have garnered considerable attention in recent years. Based on the most recent data, the average annual growth rate of housing prices in the region between 2008 and 2021 stood at approximately 10%. As an illustration, the average price per square meter in Shanghai surged from around 18,000 yuan in 2008 to approximately 60,000 yuan in 2021. The high cost of housing in the region has made it difficult for many talented individuals to afford such expenses. Consequently, talent mobility between cities may be impeded as individuals may choose to stay in areas with lower housing costs rather than relocate to cities with high housing prices. This restriction in talent mobility diminishes the exchange and sharing of knowledge among cities, thereby reducing the opportunities for knowledge spillovers.

In addition, there exists an imbalance in labor mobility among cities in the Yangtze River Delta region. Core cities such as Shanghai and Hangzhou attract a large number of high-tech talents, while smaller and medium-sized cities still face prominent talent outflow issues. This imbalance in mobility leads to resource concentration and widening development gaps between cities. Additionally, labor mobility faces certain barriers, such as the household registration system, talent recognition, social security, and other issues. These factors restrict the free mobility of labor within the Yangtze River Delta region, preventing some talents from fully realizing their potential. On the other hand, there is a relatively high level of mobility among high-tech talents in the region, but there is also a certain degree of talent loss. Some high-tech talents prefer to seek better career opportunities in developed countries or regions, resulting in a certain degree of talent outflow, which has an impact on regional technological innovation and economic development.

Given the importance of Yangtze River Delta region and the complex dynamics in human capital flow in this region, it is meaningful for us to examine how the housing price would impact regional knowledge spillovers to better understand the process and performance of knowledge spillovers in Yangtze River Delta region.

## 2. Literature Review

Knowledge spillover refers to the process in which created knowledge can be utilized by other individuals or organizations without payment or cost, due to the non-rivalrous and partially excludable nature of knowledge. This spillover effect leads to the diffusion and sharing of knowledge in society, generating positive externalities. For instance, firms or individuals gain new knowledge and technologies through their innovation activities, which may diffuse to other firms or individuals, enabling them to innovate and engage in economic activities, thus generating economic benefits.

Arrow (1962) introduced the concept of knowledge spillover, highlighting the non-rivalrous and partially excludable nature of knowledge, wherein the use of knowledge does not diminish its supply, and even with knowledge protection through intellectual property rights, knowledge producers cannot completely prevent others from freely using their knowledge. These non-rivalrous and partially excludable characteristics form the basis of knowledge spillover. Griliches (1992) further classified knowledge spillovers into vertical spillovers and horizontal spillovers. Vertical spillovers refer to the spillover effects occurring between firms due to transactional relationships. While such spillover effects are technically possible, they may not incentivize further innovation and productivity improvements for both buyers and sellers.

On the other hand, horizontal spillovers involve the transfer and sharing of knowledge, which can occur even in the absence of direct transactions or technological connections between two firms. Laursen and Salter (2006) argued that coordinating and sharing external knowledge resources alongside internal knowledge investments by firms can reduce information asymmetry related to new knowledge and enhance market access for new technologies. This suggests that firms can benefit from knowledge spillovers by engaging in knowledge exchange and collaboration with other firms, thus enhancing their innovation capabilities and competitiveness.

The role of knowledge spillovers in labor mobility has long been recognized. Audretsch et al. (1996) pointed out that the spillover effects of research and development can lead to the agglomeration of firms and industries, thereby facilitating labor inflows. Ciccone (2002) found that with increasing employment density, the effects of knowledge spillovers and human capital enhancement become evident, leading to an increase in labor productivity. Following Ciccone (2002), 'employment density' and similar indicators have become important variables in empirical studies characterizing knowledge spillovers. Ottaviano et al. (2006) adopted this measure and found a significant positive effect of employment density on labor wages, with wage changes potentially triggering labor mobility. Building on the importance of human capital in economic growth, Moretti (2004) used the proportion of urban college students to the total population as a proxy variable for urban agglomeration and found significant positive effects of knowledge spillovers resulting from urban human capital externalities on wages, thereby causing labor mobility. Chen et al. (2009), using employment density as a substitute variable for knowledge spillovers based on 2004 economic census data in Beijing, discovered a positive effect of employment density on labor productivity.

Ciccone et al. (2006) argued that knowledge spillovers occur in the unconscious interaction and communication processes among different groups, and the dissemination of these spillovers may vary among different skilled labor forces. Their empirical results revealed that high-skilled labor forces, due to their strong learning ability, benefit more from knowledge spillovers in terms of wage increases. This heterogeneity in the impact leads to heterogeneity in labor mobility. Matano et al. (2012) found that the skill composition of the labor force largely influences the impact of knowledge spillovers on wages, with a more significant effect observed on wages of high-skilled labor forces. The interaction between knowledge spillovers and industrial agglomeration may further complicate the effects on wage levels and labor mobility. For instance, Zhao et al. (2015) found that regions with greater diversity in agglomeration or industry diversity tend to benefit more from the positive effects of knowledge spillovers on wages, while regions with lower diversity in agglomeration exhibit a negative impact on wage increases. Yu et al. (2017) discovered that knowledge spillovers resulting from specialization agglomeration have a 'threshold' effect on wages of mobile populations, with a significant positive effect on high-skilled groups and a significant negative effect on low-skilled groups. Through their influence on wages of mobile populations, knowledge spillovers can impact labor mobility.

Housing serves as both a place for residence and meeting the basic living needs of workers and as a component of workers' asset allocation. These factors are the main reasons why housing prices can impact labor mobility. Helpman (1998) was one of the early contributors discussing the impact of housing prices on labor mobility. Helpman (1998) and Hanson (2005) found that housing prices would influence regional agglomeration of labor and an increase in housing prices would result in labor outflows. However, Dohmen (2005) argued that the expectation of housing price arbitrage would stimulate labor inflows. Gao et al. (2012, 2014) found that a relative increase in urban housing prices would induce labor outflows, with the restraining effect of housing prices more pronounced among rural laborers. The rise in urban housing prices poses obstacles to the inflow of rural laborers into cities. On the other hand, the widening urban-rural income gap encourages rural labor migration to cities. Fan et al. (2015) suggested that the reason why high urban housing prices did not hinder the continuous inflow of migrants was that the majority of new residents were low-skilled laborers who had less connection with housing transactions. Xia et al. (2015) discovered that housing prices 'capitalized' certain unobserved public services or urban characteristics, thereby exerting a positive effect on labor inflows. Zhang et al. (2017) found an inverted U-shaped relationship between housing prices and labor mobility, with the turning point of high-skilled laborers being relatively smaller and the turning point of labor mobility in coastal cities being larger. The increase in housing prices, through the mechanisms of cost of living and leisure substitution effects, raises wage levels. In the absence of synchronous improvement in labor productivity, enterprises strengthen their preference for capital investment over labor, thus objectively driving labor mobility (Zhang et al., 2018). Zhou et al. (2019) examined whether labor households that had ‘entered’ cities would ‘settle down’ and found that high housing prices would enhance the mobility intention of labor households, especially for those without homeownership and with high skill levels. At the same time, the probability of laborers intending to continue moving was higher toward the location of their owned housing, while the wealth effect of housing made laborers more inclined to move to other cities, particularly provincial-level and above cities.

## 3. Variable, Empirical Model and Data

In this section, we follow Ye et al. (2016) to conduct the relevant analysis.

### *3.1 Investment and Output Variables*

The whole theoretical framework to examine the input and output variables is based on Griliches-Jaffe knowledge production function (Griliches, 1979; Jaffe, 1989). In this study, we use the number of patent applications from 16 cities in the Yangtze River Delta region during 2001-2012 as a proxy for innovation output, denoted as P. Research and development (R&D) investment, including personnel and funding, is the most crucial input for knowledge production. Due to the lack of data on research institutions in each city, this paper focuses on two main types of

R&D investment entities: universities and enterprises. We investigate their respective patent outputs and spillover effects. The R&D investment of the former is measured by the science and technology funding of universities in each city, denoted as U, while the R&D investment of the latter is measured by the R&D expenditure of industrial enterprises above a certain scale in each city, denoted as R.

### *3.2 Knowledge Spillover Variables*

In addition to relying on local enterprises and universities' R&D investments, the knowledge output of a region is also influenced by knowledge spillovers from other regions, with the magnitude of the effect constrained by natural geographic distance and economic distance. To analyze the impact of the natural and economic "closeness" between cities within the Yangtze River Delta region on regional innovation output, we construct the following knowledge spillover variables.

The construction of the weighted knowledge spillover variables based on natural geography is mainly inspired by the approaches of Jaffe (1989) and Fischer and Varga (2003), refining the knowledge production function into the following basic form:

$$\boldsymbol{K_{it} = f\left(U_{i,t-q}, S^U_{i,t-p}, R_{i,t-q}, S^R_{i,t-p}, Z_{it}\right), i = 1, 2, \dots, N}$$

where $K_{it}$ represents the knowledge output of city i in year t, $U_{i,t-q}$ and $R_{i,t-q}$ represent the R&D inputs of universities and enterprises in city i in year t-q, $S^U_{i,t-p}$ and $S^R_{i,t-p}$, respectively, represent the knowledge spillover effects from universities and enterprises outside city i in year i-p, and $Z_{it}$ represents the scale and institutional factors influencing the knowledge output of city i. q and p denote the lag periods of the knowledge spillovers produced by internal R&D inputs and external R&D inputs in city i, respectively.

Following Fischer and Varga (2003), the lag period of internal R&D inputs within city i is q=2. Considering that the spillovers from innovation activities in other cities outside city i may have a longer lag period compared to the city's own R&D inputs, we assume q=3. The construction of the spillover variables is as follows:

$$\boldsymbol{U'_t = (U_{1t}, U_{2t}, \dots, U_{Nt})_{1\times N}}$$
$$\boldsymbol{R'_t = (R_{1t}, R_{2t}, \dots, R_{Nt})_{1\times N}}$$
$$\boldsymbol{D_i = (d^{-r}_{i,1}, \dots, d^{-r}_{i,i-1}, 0, d^{-r}_{i,i+1}, \dots, d^{-r}_{i,N})_{1\times N}}$$

where $U'_t$ and $R'_t$ represent the R&D input matrices of universities and enterprises in a $1 \times N$ city matrix. $D_i$ represents the matrix of natural geographic distances between city i and other cities, and $d_{ij}$ represents the straight-line distance between city i and city j. r>0 is a distance decay parameter. A larger value of r implies a smaller knowledge spillover effect, indicating a weaker impact on city knowledge output. The calculation of the spillover variables for both sectors is as follows:

$$\boldsymbol{S^U_{it} = D_i U_t}$$
$$\boldsymbol{S^R_{it} = D_i R_t}$$

$d_{ij}$ the data is based on measurements from Google Maps, and in the subsequent regression analysis, r takes a value of 0.51.

Following Ye et al. (2016), the construction of weighted knowledge spillover variables based on economic geography is mainly inspired by Greunz (2003), who applied Jaffe's (1986) concept of technological similarity to the regional level to measure the similarity of technological structures between two regions. First, the technological similarity index is constructed as follows:

$$\boldsymbol{t_{ij} = \frac{\sum_{k=1}^{122} f_{ik} f_{jk}}{\sqrt{\sum_{k=1}^{122} f_{ik}^2 \sum_{k=1}^{122} f_{jk}^2}}}$$

where k represents each of the 122 three-digit International Patent Classification (IPC) code of the patents, and $f_{ik}$ represents the number of patents in the i-th city in the k-th IPC class as a share of the total number of patents in that class within the region.

Similar to $S_{it}^{U}$ and $S_{it}^{R}$, we construct knowledge spillover indicators, $T_{it}^{U}$ and $T_{it}^{R}$, weighted by the technological similarity index and calculated as follows:

$$\boldsymbol{T_i = (t_{i,1}, \dots, t_{i,i-1}, 0, t_{i,i+1}, \dots, t_{i,N})}$$
$$\boldsymbol{T_{it}^{U} = T_i U_t}$$
$$\boldsymbol{T_{it}^{R} = T_i R_t}$$

Although there is a high correlation between industrial structure and technological structure, examining the economic proximity between cities from the perspective of industrial structure still holds independent value from the perspective of technological structure. Therefore, following the calculation of the technological similarity index, we construct an industrial similarity index using the output data of various sub-industries in each city's manufacturing sector. Manufacturing is a crucial component of the industry, and the industrial similarity index constructed based on manufacturing output data can partially reflect the similarity of industrial structures between two regions. Similar to the technological similarity index, the calculation formula for the industrial similarity index is as follows:

$$\boldsymbol{m_{ij} = \frac{\sum_{k=1}^{30} f_{ik} f_{jk}}{\sqrt{\sum_{k=1}^{30} f_{ik}^2 \sum_{k=1}^{122} f_{jk}^2}}}$$

where k represents the manufacturing industry sectors classified according to the 30 two-digit codes of the 2002 National Economic Industry Classification Standard, $f_{ik}$ denotes the total industrial output value of industry k in city i. The spillover variables weighted by industry similarity index $M_{it}^{U}$ and $M_{it}^{R}$ are constructed as follows:

$$\boldsymbol{M_i = (m_{i,1}, \dots, m_{i,i-1}, 0, m_{i,i+1}, \dots, m_{i,N})}$$
$$\boldsymbol{M_{it}^{U} = M_i U_t}$$
$$\boldsymbol{M_{it}^{R} = M_i R_t}$$

### *3.3 Housing price*

We want to explore how the housing price would impact the knowledge spillovers. In this paper, we therefore utilize panel data consisting of annual average transaction prices of residential properties for the sample cities.

### *3.4 Other Control Variables*

The overall economic scale of a region and foreign direct investment (FDI) are important factors influencing innovation and knowledge output in a region. We control for these two factors by including per capita GDP and actual utilization of FDI. Industrial agglomeration may also affect regional innovation and knowledge output. We introduce the Herfindahl-Hirschman Index (HHI), commonly used in industrial economics and regional economics, to control for the impact of the degree of industrial diversification or specialization on innovation and knowledge output in each city. The formula for constructing this index is as follows: $HHI_i = \sum_{k=1}^{n} \left(\frac{G_{ik}}{G_i}\right)^2$, where $G_{ik}$ is the total industrial output of industry k in region i, and $G_i$ is the total industrial output in region i. The higher the value of HHI, the higher the degree of industrial specialization in the region, and the lower the value, the higher the degree of industrial diversification in the region.

### *3.5 Empirical model*

We construct the following models to estimate the effect of housing price on knowledge spillovers.

$$\log S_{i,t-3}^{R} = a_0 + a_1 \log R_{i,t} + a_2 \log U_{i,t} + a_3 \log Hprice_{i,t} + a_4 \log GDP_{i,t} + a_5 \log FDI_{i,t} + a_6 HHI_{i,t} + city_i + \varepsilon_{it} \quad (1)$$

$$\log S_{i,t-3}^{U} = a_0 + a_1 \log R_{i,t} + a_2 \log U_{i,t} + a_3 \log Hprice_{i,t} + a_4 \log GDP_{i,t} + a_5 \log FDI_{i,t} + a_6 HHI_{i,t} + city_i + \varepsilon_{it} \quad (2)$$

$$\log T_{i,t-3}^{R} = a_0 + a_1 \log R_{i,t} + a_2 \log U_{i,t} + a_3 \log Hprice_{i,t} + a_4 \log GDP_{i,t} + a_5 \log FDI_{i,t} + a_6 HHI_{i,t} + city_i + \varepsilon_{it} \quad (3)$$

$$\log T_{i,t-3}^{U} = a_0 + a_1 \log R_{i,t} + a_2 \log U_{i,t} + a_3 \log Hprice_{i,t} + a_4 \log GDP_{i,t} + a_5 \log FDI_{i,t} + a_6 HHI_{i,t} + city_i + \varepsilon_{it} \quad (4)$$

$$\log M_{i,t-3}^{R} = a_0 + a_1 \log R_{i,t} + a_2 \log U_{i,t} + a_3 \log Hprice_{i,t} + a_4 \log GDP_{i,t} + a_5 \log FDI_{i,t} + a_6 HHI_{i,t} + city_i + \varepsilon_{it} \quad (5)$$

$\log M^U_{i,t-3} = a_0 + a_1 \log R_{i,t} + a_2 \log U_{i,t} + a_3 \log Hprice_{i,t} + a_4 \log GDP_{i,t} + a_5 \log FDI_{i,t} + a_6 HHI_{i,t} + city_i + \varepsilon_{it}$ (6)

***3.6 Data***

We select 16 cities in the Yangtze River Delta region as the target cities. These cities are Shanghai, Wuxi, Suzhou, Yangzhou, Taizhou, Ningbo, Huzhou, Zhoushan, Nanjing, Changzhou, Nantong, Zhenjiang, Hangzhou, Jiaxing, Shaoxing, and Taizhou. The time period is from 2001 to 2019. All the data in this study were collected from "China City Statistical Yearbook," "Shanghai Statistical Yearbook," "Jiangsu Statistical Yearbook," "Zhejiang Statistical Yearbook," "Compilation of Statistics on Science and Technology in Higher Education," the statistical yearbooks of respective cities, and the patent database published by the National Intellectual Property Administration. To eliminate the influence of price factors, per capita GDP, FDI, local government expenditure on science and technology, R&D expenditure of large-scale enterprises, and other data from each city were adjusted using the GDP deflator of each province, with the base year set as 2001.

## 4. Main Results

| | (1) $\log S^R_{i,t-3}$ | (2) $\log S^U_{i,t-3}$ | (3) $\log T^R_{i,t-3}$ | (4) $\log T^U_{i,t-3}$ | (5) $\log M^R_{i,t-3}$ | (6) $\log M^U_{i,t-3}$ |
|---|---|---|---|---|---|---|
| Enterprise R&D | 0.185* | 0.195* | 0.190* | 0.196* | 0.263*** | 0.258*** |
| | (0.098) | (0.098) | (0.098) | (0.096) | (0.075) | (0.071) |
| University R&D | 0.019** | 0.020** | 0.024* | 0.025** | 0.053 | 0.024 |
| | (0.010) | (0.010) | (0.013) | (0.011) | (0.092) | (0.093) |
| Housing price | -0.017** | -0.013 | -0.015*** | -0.023*** | -0.044 | -0.022** |
| | (0.007) | (0.011) | (0.004) | (0.007) | (0.036) | (0.010) |
| Other variables controlled | Yes | Yes | Yes | Yes | Yes | Yes |
| City fixed | Yes | Yes | Yes | Yes | Yes | Yes |
| R-sq | 0.901 | 0.901 | 0.900 | 0.902 | 0.979 | 0.980 |

**Table 1. Baseline panel data results**

Note: The values in parentheses are standard deviations. *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively.

Table 1 reports the regression results of models (1)-(6). We can see that the results indicate the role of housing price is significant for most of the spillover forms, while the signs of the coefficients are as expected. We therefore confirm the potential negative effects of housing price on the knowledge spillovers in Yangtze River Delta region.

We have done several robustness checks. First, we used one period lagged housing price as an instrumental variable and conducted the IV estimation. Our main findings still hold. Second, we added the R&D spending of local governments as the additional control variable and conducted the analysis in Table 1 again. Our main findings also hold.

## 5. Conclusion

By the above analysis, we have empirically shown the possibility that the housing price can negatively impact knowledge spillovers in Yangtze River Delta region. The government ought to implement policies aimed at increasing the availability of affordable housing in the region. This can be accomplished by offering incentives to developers for the construction of affordable housing units or by providing subsidies to low-income individuals and families. By ensuring housing affordability, the region can facilitate the flourishing of skilled workers and innovative businesses, thus promoting the occurrence of knowledge spillover. Furthermore, it is crucial for the government to prioritize balanced regional development and allocate resources towards infrastructure projects that enhance connectivity between cities within the Yangtze River Delta region. This approach can help mitigate the concentration of economic activities in a few major cities and foster opportunities for knowledge spillover throughout the entire region. Enhancements in transportation, communication, and collaboration platforms can play a significant role in facilitating the exchange of ideas and knowledge among cities. Additionally, the government should offer tailored support and incentives specifically designed to assist small and medium-sized enterprises (SMEs) and start-ups in overcoming the challenges posed by high housing prices. These measures could encompass the establishment of affordable co-working spaces or innovation hubs, increased access to funding and resources, and the implementation of mentorship programs. By nurturing an environment that is conducive to the growth of these enterprises, the government can effectively promote knowledge spillover and the diffusion of innovation.

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